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International Journal of Combinatorial Optimization Problems and Informatics, 17(2), 2026, 283-295. ISSN: 2007-1558. https://doi.org/10.61467/2007.1558.2026.v17i2.1192

Development of a Genetic Algorithm for the Formation of Sports Teams

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Abstract. This project addresses a significant challenge in the formation of sports teams within the university environment of the Reynosa Rodhe Multidisciplinary Academic Unit (UAMRR) of the Autonomous University of Tamaulipas (UAT). The project identifies the need to establish balanced and competitive teams that reflect the diversity of skills in sports activities. The project proposes the development of a genetic algorithm aimed at the automatic generation of optimal sports teams using techniques based on natural evolutionary processes, such as selection, crossing, and mutation. This algorithm is integrated into a web application with a database that stores detailed information about the students. It is developed in an intuitive design to ensure an optimal user experience and facilitate application navigation.

Keywords: Genetic Algorithms, Database, Programming Language, Web Application.

Article Info
Received July 31, 2025
Accepted Dec 12, 2025

1 Introduction

Genetic algorithms (GAs) are distinguished by their ability to evaluate a wide range of values and compare them with each other, using a probabilistic approach. Their main objective is to identify the best possible solution, which is expected to resemble or achieve the global maximum value. GAs differentiates them from other optimization methods by their inspiration in the processes of natural selection, which involves the creation of an initial population that represents multiple points in the search space (Ruge and Alvis, 2009).

These algorithms have been successfully applied in highly complex engineering contexts, such as the automatic generation of equipment in senior settings. Specifically, in residential and day care centers, based on group formation, using a structure-generating approach. The results obtained indicate near-optimal solutions in all the proposed scenarios, with a notable improvement in execution time compared to approaches based on linear programming (Hernandez Montesino, 2016).

Another example of the effectiveness of genetic algorithms is their application to automatically generate work teams in educational settings. The task of forming balanced teams in the educational field presents a significant challenge due to the vast number of possible combinations, making it virtually impossible to solve. The timescales and results obtained have been quite positive, thus meeting the needs inherent to the problem (Chacon Martinez, 2018).

Genetic algorithms are a powerful tool for solving complex problems, offering an efficient way to explore solutions in large search spaces and address challenges beyond the capabilities of traditional approaches. Their inspiration in natural evolution and their versatility make them essential for optimization and decision-making in a wide variety of fields.

In this research, the developed genetic algorithm focuses on the formation of sports teams and can be used in various disciplines such as soccer, volleyball, American football, and baseball. The research conducted did not uncover significant information on algorithms that address team formation in a multidisciplinary sports environment. Some algorithms focus on a specific discipline, such as the work titled "Genetic Algorithms for Variable Selection in Baseball Game Prediction" by the Polytechnic

School of Madrid, which primarily aims to predict baseball game outcomes rather than team formation. Furthermore, this methodology implements predictive models using genetic algorithms (Vázquez Fernández de Lezeta, 2015). Therefore, this research aims to contribute significantly to generating more solutions in the field of sports team formation. Table 1 shows the contribution of each of the mentioned works, including this research.

Table 1. Comparative table of our research work in relation to others already mentioned

Research work	Focus on	Methodology	Contribution
Genetic algorithm for the automatic generation of teams in senior living environments	Healthcare sector	Genetic algorithms	Assignment of activities to each member
Genetic algorithm for the automatic generation of work teams in educational environments	Education sector	Genetic algorithms	Generation of heterogeneous teams in the classroom
Genetic algorithms for variable selection in baseball game prediction	Sports sector	Genetic Algorithms and Predictive Models	Generating possible results for the baseball teams that are facing each other.
Development of a genetic algorithm for the formation of sports teams	Sports sector	Genetic algorithms	Sport teams optimal formation

The proposed genetic algorithm was developed in the following scenario: In the athletic environment of the Reynosa Rodhe Multidisciplinary Academic Unit (UAMRR) of the Autonomous University of Tamaulipas (UAT), a significant and complex challenge is faced in the formation of sports teams with students. Creating balanced and competitive teams that reflect the diversity of students' abilities is essential to promote active and satisfactory sports participation. However, the manual formation of sports teams becomes an arduous and subjective task that often fails to maximize efficiency, equity, and student-athlete satisfaction. Traditional methods based on the experience and intuition of those in charge of this task can result in unbalanced teams, which affects the quality of the students' sports experience. In this context, this research proposes the development of a genetic algorithm that allows for the automatic creation of sports teams at the UAMRR. This algorithm should effectively address the complexity of decision-making by considering multiple variables such as strength, endurance, speed, flexibility, coordination, and balance, while seeking to maximize student-athlete satisfaction and equity. The solution to this problem will not only facilitate the formation of more balanced and competitive sports teams but will also optimize resource management and the quality of the students' sports experience, thus improving the management of student sports teams.

2 Experimental procedures

2.1 Delimitation of variables

The delimitation of the variables used in this research can be seen in Table 2:

Table 2. Delimitation of variables.

Variable	Conceptual Definition	Operational Definition	Dimensions	Indicators	Unit of measurement	Scale	Final Value
Time delay in generating teams	The efficiency and speed with which the system generates a sport team	Time interval, which elapses from the moment a user submits a request to generate a specific sport team, and the system generates it and displays it to the user	Temporality	Delay time between the request and the delivery of the result	Time	Seg.	High: 60 Medium: 40 Low: 1
Total team evaluation	Quality of the team formed evaluated by the objective function	Average of the total rating of the players that forming the team	Quality	Quality score	N/A	N/A	Outstanding: 8.5 Acceptable: 6.0 No acceptable: 5.9

2.2 Logical operation of the system

To carry out this project, the web application is developed in Visual Studio, using a Microsoft SQL database to manage and store user data. The application is accessible on both mobile devices and desktop computers. Figure 1 shows the application's operating system diagram.

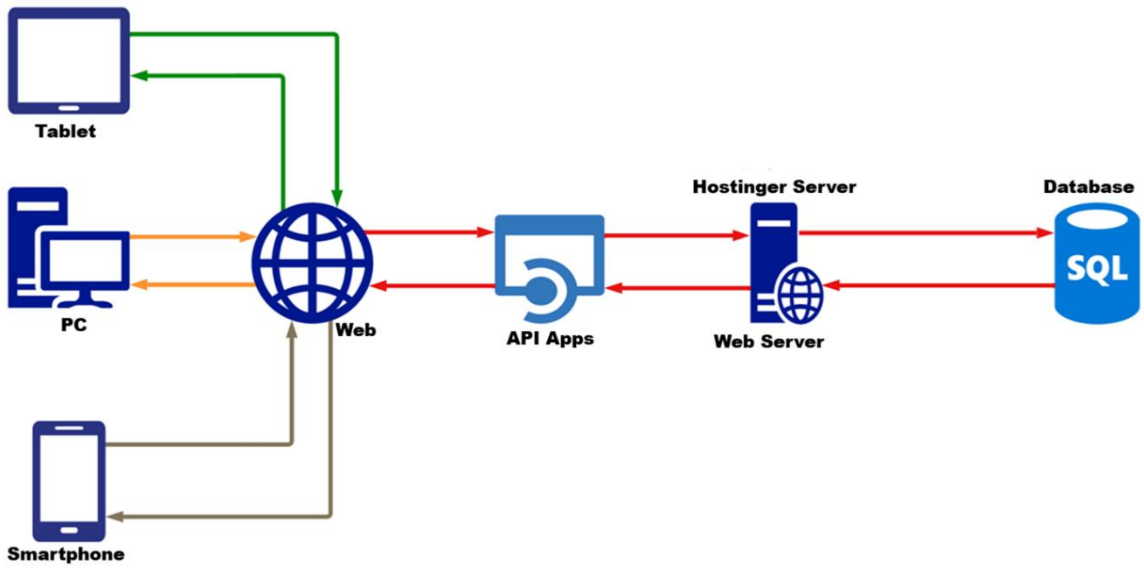

Fig. 1. Diagram of the operation of the web application.

2.3 Database design

The database architecture is structured around two crucial tables to ensure optimal application performance.
Figure 2 shows the database user table, which is used to effectively manage authorized users. Its fields include user ID, username, email address, and password. Security and unique identification for each user are prioritized to ensure comprehensive control of system access.

	Id	NombreUsuario	Correo	Contraseña	Rol
	1	juan123 ...	juan123@gma...	******	Usuario
	2	koke ...	koke@gmail.co...	******	Usuario

Fig. 2. Example of the user table in the database.

Figure 3 shows the student table in the database, which plays a central role in the system, as it constitutes the list of students with whom the genetic algorithm interacts to generate the optimal sport team. Its fields include identification (ID), registration number, name, gender, strength, speed, flexibility, coordination, and balance. The inclusion of these specific attributes allows the genetic algorithm to perform detailed evaluations for team formation.

	Id	Matricula	Nombre	Sexo	Fuerza	Resistencia	Velocidad	Flexibilidad	Coordinacion	Equilibrio
1	1	2021001	Ana López	F	80	70	65	75	85	90
2	2	2021002	Carlos Rodríguez	M	90	75	70	80	75	80

Fig. 3. Example of the student table in the database.

In the context of genetic algorithm experimentation, this table was populated with 900 fictitious student data records. These records contain varied names and random values for the physical variables, spanning a range from 0 to 100. This approach guarantees the data diversity necessary for the robustness and effectiveness of the genetic algorithm in generating sports teams.

2.4 Genetic Algorithm Design

Representation of the operation of the genetic algorithm: Figure 4 graphically shows the operation of the genetic algorithm proposed in this research work.

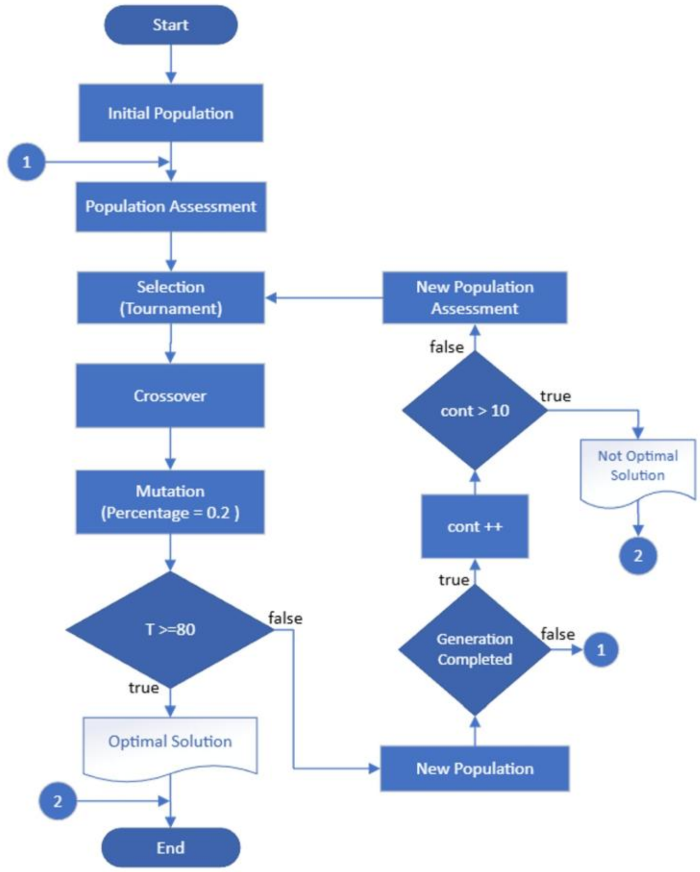

Fig. 4. How the genetic algorithm works.

Objective function: The objective function evaluates the suitability of the solution (sports teams), carefully considering the physical characteristics of the students.
Since there is no universally accepted formula for evaluating a player's performance, the approach was based on the methodology used by sports management simulators such as Football Manager. These simulators assign numerical parameters to various players' physical abilities, subsequently calculating an average as an indicator of overall performance, as can be seen in Eq. (1).

$$T = \frac{\sum_{i=1}^{N}[(F_i + R_i + V_i + Fx_i + C_i + E_i)/6]}{N} \quad \textbf{Eq. (1)}$$

Where:

T = Team performance indicator, the team is made up of N players
F = Player strength.
R = Player stamina.
V = Player speed.
Fx = Player flexibility.
C = Player coordination.
E = Player balance.
i = Individual Player
N = Total numbers of Players

The goal is to maximize the objective function T to find a team with the best possible score.

Individual: In GAs, the term "Individual" refers to the set of elements (genes) selected from a total population to solve a problem. In this study, it refers to the possible combinations that can be obtained to form an optimal team. The size of the population is a parameter that significantly influences the search for the optimal solution. When the number is small, there is limited diversity in the proposed solutions. Conversely, an excessively large population requires a substantial consumption of computational resources to address the problem.

Within the scope of this project, different numbers of individuals (teams) were experimented with, as well as different numbers of people (population) in the database. Figure 5 shows some examples of the population composition, where each set of values represents an individual (a team) made up of several players (genes).

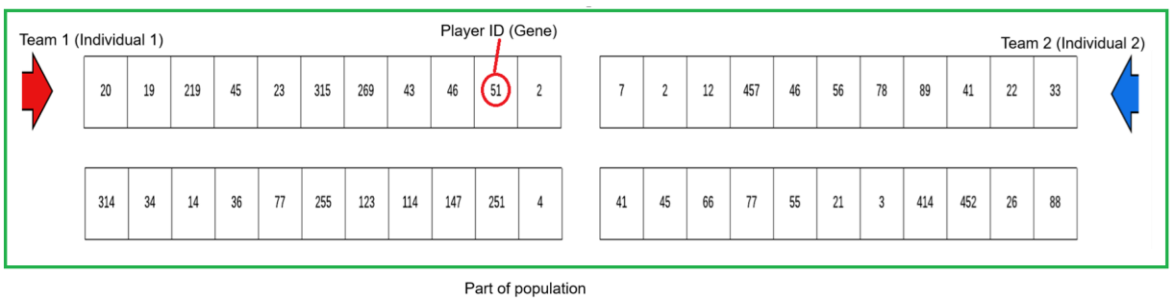

Fig. 5. Elements that made up the population in AG

Individuals, also called solutions in GA, are generated from a set of players specifically adapted to the sport in question. Figure 5 shows four representations of different teams, where each number represents a player's unique identification (ID). Clearly, a single team cannot have players with duplicate IDs

Selection: For the selection phase, several methods are possible, including tournament, roulette, elite, and rank-based selection, among others (Arranz de la Peña & Parra Truyol, 2007). This algorithm implements the tournament selection method because it allows for more equitable participation of the entire population and promotes genetic diversity, prioritizing individuals with the best physical fitness.

The process begins with the random selection of 4 individuals or teams from the current population, as shown in Figure 6.

These four teams are paired to determine the parent teams, one per pairing, by comparing the value of their team performance indicator (T). Parent 1 and Parent 2 are accordingly selected, and they will transmit their genes to subsequent generations. The winning individuals can be seen in Figure 7.

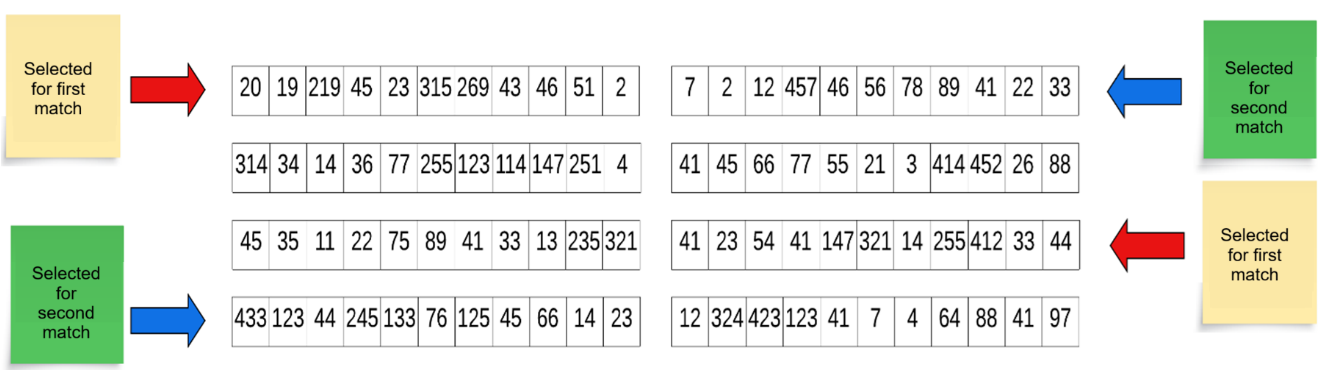

Fig. 6. Graphic Representation of Selection of Contenders for Matches.

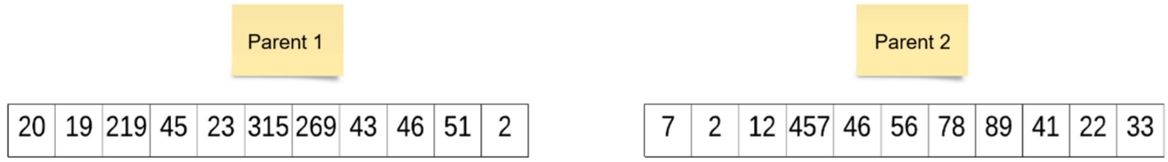

Fig. 7. Graphical representation of winning solutions to confrontations.

Crossover: In the context of this project, the single-point crossover method was chosen due to its beneficial properties. This method works by dividing an individual's coded representation into two parts, with the resulting offspring inheriting a portion from each parent.

In the specific application of this project, the cutoff point is randomly set and can take values ranging from 2 up to the total number of genes minus one. For example, in the case of a soccer team, the range would be from 2 to 10, since a soccer team is composed of 11 players. The parent teams give rise to a new team, the child, thereby ensuring the exclusivity of the genes (team members). Parent 1 provides the genes up to the cutoff point, while Parent 2 provides the genes necessary to complete the team size.

Figure 8 shows the implementation where the cutoff point used is 5. The first parent provides the first 5 genes for the child, while the second parent provides the remaining genes to complete the team size.

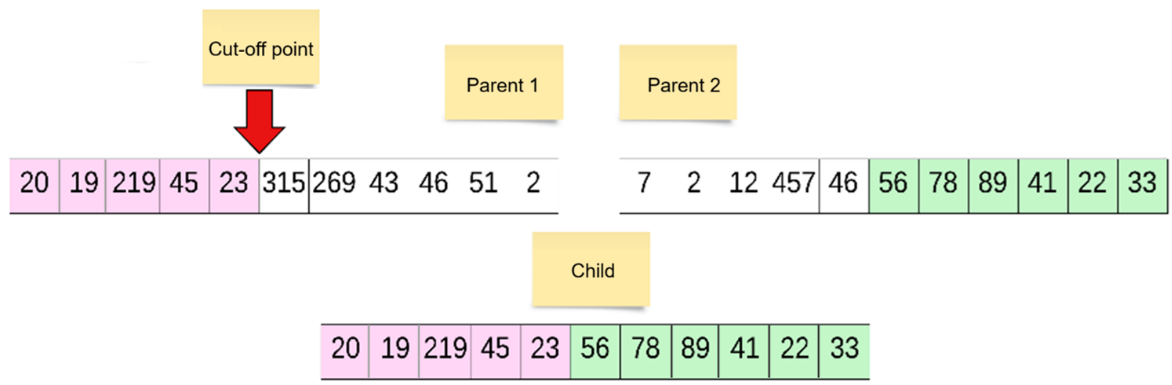

Fig. 8. Graphical Representation of SinglePointCrossover applied to the Project.

Mutation: Mutation in a genetic algorithm is defined as the probability of altering a gene in the genome to introduce greater variability into the solutions. In instances of very low probabilities, there is a risk that the algorithms become trapped in local maximum, while at high probabilities, the time required to find the solution can increase significantly, for this project, a probability value of 0.2 is determined to ensure optimal performance. The mutation strategy implemented in this project involves replacing a player in the descendant (child) team. For the mutation process, a value from 0 to 1 is randomly determined. If this value is less than or equal to 0.2, a mutation is performed; if the resulting value is greater than 0.2, the mutation is not carried out. To perform the mutation, a player is randomly selected from the child team and replaced with a player randomly selected from the entire database. It is crucial to emphasize that duplication is carefully managed; if the selected player is already part of the team, another player is selected iteratively until a player not currently on the team is found and can be added as shown in Figure 9.

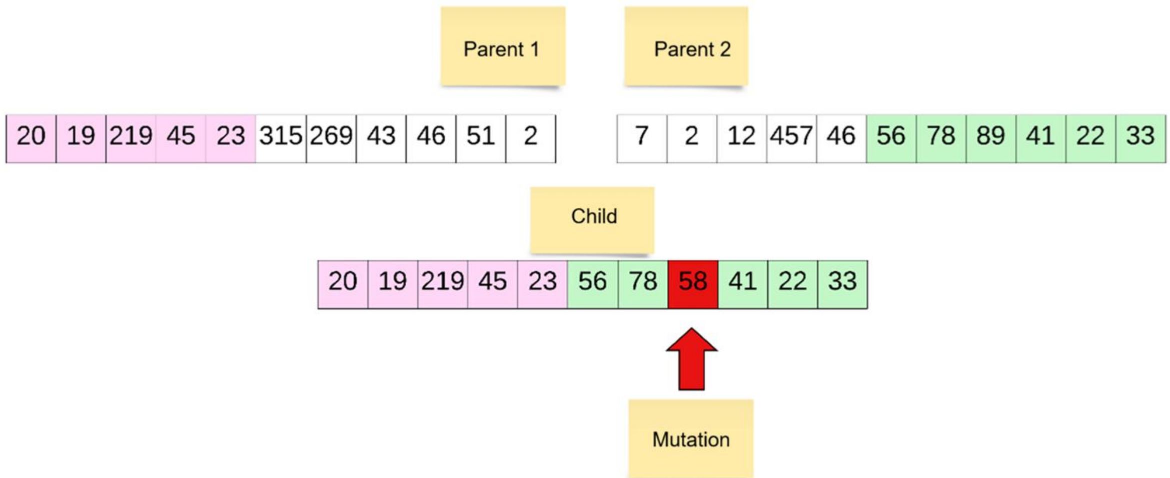

Fig. 9. Graphical representation of when the mutation occurs.

Once the mutation has been performed, the objective function is used again to calculate the team performance indicator (T) of the mutated individual. If the value of T is less than 80 points, the genes that make up the individual are used to generate a new population. If, after all selections per tournament and working up to the mutation, an individual is not found that meets the requirement of achieving a performance score of 80 or higher, the entire procedure is repeated, from generating new individuals to the mutation, but now starting with this new population generated from the mutated individuals, in order to find an individual that meets the condition of $T \geq 80$.

Stopping Conditions: The algorithm incorporates two stopping conditions to prevent the unnecessary use of computational resources. The established conditions are: 1) After 10 generations have elapsed without finding an individual that meets the condition $T \geq 80$; 2) when a mutated individual is found that meets the condition $T \geq 80$.

This approach ensures that a team with acceptable and balanced performance is formed.

2.5 Experimentation with the Genetic Algorithm

For the experimental process, the database with the previously mentioned design was used. This database was generated with fictitious information for the purpose of testing the algorithm; this fact does not affect the algorithm's performance when the data is real. The test database consists of 900 students, both male and female, organized as shown in Figure 10.

Two members with perfect scores were added, one male named "Jorge Ramos" and one female named "Melanie Ramos" both having 100 in all characteristics to ensure that the best members are selected.

First round of algorithm testing:
In the first round of testing, it was decided to generate both female and male soccer teams, with 11 players per team per generation, obtaining the results shown in tables 3 and 4.

Id	Matricula	Nombre	Sexo	Fuerza	Resistencia	Velocidad	Flexibilidad	Coordinación	Equilibrio
1	2021001	Ana López	F	80	70	65	75	85	90
2	2021002	Carlos Rodríguez	M	90	75	70	80	75	80
3	2021003	María Pérez	F	70	60	80	70	85	75
4	2021004	Juan Martínez	M	85	90	60	75	70	65
5	2021005	Luisa Sánchez	F	100	100	100	100	100	100
6	2021006	Miguel Torres	M	80	75	75	70	90	80
7	2021007	Elena García	F	85	80	75	65	70	80
8	2021008	Pedro Ramírez	M	70	85	85	80	60	70
9	2021009	Isabel Gómez	F	75	70	70	90	80	85
10	2021010	Javier Vargas	M	90	80	80	75	70	75
11	2021001	Juan Pérez	M	85	70	65	75	80	85
12	2021002	Ana López	F	70	75	70	90	65	80
13	2021003	Carlos Rodríguez	M	90	80	60	70	75	70
14	2021004	María Gómez	F	75	85	75	77	55	55
15	2021005	Luis Martínez	M	80	60	80	65	90	60
16	2021030	Laura Ramírez	F	70	75	85	80	75	70
17	2021030	Carmen Silva	F	80	75	65	85	70	90
18	2022009	Miguel Torres	M	85	60	75	80	70	65
19	2022010	Laura Díaz	F	10	20	30	20	55	50
20	2022011	Jorge RamosSSs	M	100	100	100	100	100	100
21	2022012	Sara González	F	78	65	80	75	85	90
22	2022013	Héctor Ramírez	M	88	77	72	81	55	81
23	2022014	Marina Martínez	F	68	44	78	68	88	73
24	2022015	Pablo Gómez	M	92	82	70	90	78	65
25	2022016	Leticia Sánchez	F	82	75	65	80	90	80
26	2022017	Jorge Pérez	M	75	90	75	70	85	75
27	2022018	Cristina Vargas	F	70	80	55	75	75	70
28	2022019	Martín Martínez	M	85	11	70	80	80	90
29	2022020	Beatriz Ramírez	F	90	44	80	85	70	75
30	2022021	Sergio Silva	M	80	85	65	70	90	80
31	2022022	Lucía Torres	F	75	70	75	90	80	85
32	2022023	Diego Pérez	M	90	80	80	75	70	75
33	2022024	Eva González	F	85	70	65	75	80	85
34	2022025	Adrián Rodríguez	M	70	75	70	90	65	80
35	2022026	Paula Díaz	F	90	80	60	70	75	70
36	2022027	Álvaro Martínez	M	75	11	55	95	70	75
37	2022028	Silvia Sánchez	F	80	60	80	55	90	60
38	2022029	Raúl Ramírez	M	70	75	85	80	75	70

20 of 200 Cell is Modified.

Fig. 10 Student data table.

Table 3 Execution of algorithm for men's soccer team.

Players Total group score: 84.45			Stopped in generation 43		Soccer					
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
122	2022121	Diego López	M	89	82	76	88	82	90	84
342	2022341	Daniel Gómez	M	88	85	76	80	78	82	81
90	2022089	Diego Martinez	M	89	82	76	88	82	90	84
102	2022101	Adrián Ramírez	M	88	79	74	85	80	88	82
104	2022103	Iván Martinez	M	87	80	75	86	81	86	82
20	2022011	Jorge Ramos	M	100	100	100	100	100	100	100
138	2022137	Jorge Rodríguez	M	89	82	76	88	82	90	84
86	2022085	Manuel Ramírez	M	88	86	74	85	80	88	83
166	2022165	Adrián Ramírez	M	88	79	74	85	80	88	82
200	2022199	Alexis Mancilla	M	87	80	75	86	81	86	82
210	2022209	Leonardo Gómez	M	88	85	76	80	78	80	81

Table 3 shows the male player "Jorge Ramos" and Table 4 the female player "Melanie Ramos." Both are consistently present in the selected team, given that they significantly raise the rating by maintaining a perfect score in their statistics. Both teams show a good alignment with the essential physical characteristics for soccer.

However, according to Table 3, the men's team seems to be better balanced in terms of total score, while according to Table 4, the women's team, although competitive, has greater diversity in individual skills. These results highlight the effectiveness of the algorithm to form balanced teams.

Table 4 Execution of algorithm for women's soccer team.

Players Total group score: 81.09		Stopped in generation 52			Soccer					
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
31	2022022	Lucia Torres	F	75	70	75	90	80	85	79
407	2022406	Marina Sánchez	F	78	72	75	84	82	80	78
173	2022172	Marina Diaz	F	78	65	80	75	85	90	78
201	2022120	Melanie Ramos	F	100	100	100	100	100	100	100
21	2022012	Laura Gonzales	F	78	65	80	75	85	90	78
91	2022090	Carmen Silva	F	79	89	71	80	91	80	81
189	2022188	Sara Gonzales	F	78	65	80	75	85	90	78
72	2022063	Lucia Torres	F	75	70	75	90	80	85	79
47	2022038	Luisa Ramírez	F	85	70	70	80	80	90	79
70	2022061	Beatriz Ramírez	F	90	75	80	85	70	75	79
66	2022057	Leticia Sánchez	F	82	75	65	80	90	80	78

Continuing with the experimentation with teams from other disciplines, it was decided to generate male and female basketball teams, with 5 players each per generation.

Table 5 Algorithm execution for the Men's Basketball team.

Players Total group score: 87.40		Stopped in generation 43			Basketball					
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
122	2022121	Diego López	M	89	82	76	88	82	90	84
90	2022089	Diego Martinez	M	89	82	76	88	82	90	84
86	2022085	Manuel Ramírez	M	88	86	74	85	80	88	83
138	2022137	Jorge Rodríguez	M	89	82	76	88	82	90	84
20	2022011	Jorge Ramos	M	100	100	100	100	100	100	100

Table 5 and Table 6 show the results of running the genetic algorithm to form basketball teams, both for men and women. The results reflect how the players' physical characteristics align with the sport's requirements.

Table 5 shows how, for the men's team, the algorithm stopped at generation 43, achieving a total score of 87.40. This team demonstrates consistency in physical characteristics, with high average scores across all skills, especially strength and balance.

Table 6 Execution of algorithm for women's basketball team.

Players Total group score: 83.633			Stopped in generation 32			Basketball				
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
201	2022120	Melanie Ramos	F	100	100	100	100	100	100	100
109	2022208	Susana González	F	78	69	80	75	85	90	79
80	2022071	Marina Silva	F	82	89	76	72	87	78	80
70	2022061	Beatriz	F	90	75	80	85	70	75	79
125	2022124	Carmen Sánchez	F	78	65	80	75	85	90	78

Second round of algorithm testing: In the second round of testing, it was decided to run the algorithm for volleyball with 6 players each per generation.

Table 7 and Table 8 show that both teams have a high level of preparation and balance in the physical skills required for volleyball. The algorithm has proven effective in forming competitive teams, with a slight advantage in the consistency of scores for the men's team according to Table 7.

These results underline the algorithm's ability to select players who are not only physically fit, but also well adapted to the specific demands of volleyball. In these particular scenarios, the algorithm required more time to reach the optimal solution, evaluating around 160,000 possible solutions.

Table 7 Algorithm execution for the men's volleyball team.

Players Total group score: 86.77			Stopped in generation 19			Volleyball				
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
20	2022011	Jorge Ramos	M	100	100	100	100	100	100	100
90	2022089	Diego Martinez	M	89	82	76	88	82	90	84
122	2022121	Diego López	M	89	82	76	88	82	90	84
148	2022147	Daniel Gómez	M	86	96	73	84	79	84	83
138	2022089	Jorge Rodríguez	M	89	82	76	88	82	90	84
86	2022085	Manuel Ramírez	M	88	86	74	85	80	88	83

Table 8 Algorithm execution for the women's volleyball team.

Players Total group score: 83.36			Stopped in generation 20		Volleyball					
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
201	2022120	Melanie Ramos	F	100	100	100	100	100	100	100
109	2022	Susana Gonzales	F	78	69	80	75	85	90	79
80	2022	Marina Silva	F	82	89	76	72	87	78	80
47	2022	Luisa Ramírez	F	85	70	70	80	80	90	79
70	2022	Beatriz Ramírez	F	90	75	80	85	70	75	79
91	2022	Carmen Silva	F	79	89	71	80	91	80	81

Third round of algorithm testing: As a final round of testing, it was decided to test the algorithm in extreme stress cases with men's baseball and women's softball, with 9 players each per generation.

This was to verify its performance in these extreme cases, which are not feasible for other search strategies.

Table 9 Algorithm execution for the men's baseball team.

Players Total group score: 85.46			Stopped in generation 27		Baseball					
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
20	2022011	Jorge Ramos	M	100	100	100	100	100	100	100
122	2022121	Diego López	M	89	82	76	88	82	90	84
138	2022089	Jorge Rodríguez	M	89	82	76	88	82	90	84
148	2022147	Daniel Gómez	M	86	96	73	84	79	84	83
86	2022085	Manuel Ramírez	M	88	86	74	85	80	88	83
120	2022119	Iván Rodríguez	M	87	80	75	86	81	86	82
52	2022043	Javier Martinez	M	85	87	86	75	80	85	83
152	2022151	Giovani Rentería	M	87	80	75	86	84	86	83
90	2022089	Diego Martinez	M	89	82	76	88	82	90	84

In this particular scenario according to Table 9 and Table 10, the algorithm has proven to be effective in forming teams with a high and balanced score in both sports.

Table 10 Algorithm execution for the Women's Softball team.

Players Total group score: 83.36		Stopped in generation 20		Softball						
Id	Student ID Number	Name	Gender	Strength	Endurance	Speed	Flexibility	Coordination	Balance	Fitness
201	2022120	Melanie Ramos	F	100	100	100	100	100	100	100
91	2022090	Carmen Silva	F	79	89	71	80	91	80	81
47	2022038	Luisa Ramírez	F	85	70	70	80	80	90	79
72	2022063	Lucia Torres	F	75	70	75	90	80	85	79
41	2022032	Ana Martinez	F	88	77	72	81	76	81	79
70	2022061	Beatriz Ramírez	F	90	75	80	85	70	75	79
31	2022022	Lucia Torres	F	75	70	75	90	80	85	79
80	2022071	Marina Silva	F	82	89	76	72	87	78	80
109	2022108	Susana Gonzales	F	78	69	80	75	85	90	79

3 Results

After conducting multiple tests that included diverse population configurations and variations in the number of players per team, the feasibility of exploring up to 20,000 different team configurations was confirmed. Consequently, it has been established that the problem can be satisfactorily solved by applying genetic algorithms, achieving time efficiency and reduced consumption of computational resources.

Table 11 Final Results.

Test	Population	Sport	Number of students in the database	Time	Revised equipment configurations	Team rating
1	100	Soccer M	900	1.1 S	4,300	84.45
2	100	Soccer F	900	1.4S	5,200	81.09
3	200	Basketball M	900	2.0 S	8,600	87.4
4	200	Basketball F	900	1.5 S	6,400	83.63
5	8000	Volleyball M	900	20 S	152,000	86.77
6	8000	Volleyball F	900	22 S	160,000	83.36
7	20 000	Baseball M	900	50 S	540,000	85.46
8	20 000	Softball F	900	50 S	520,000	81.96

As Table 11 shows, the algorithm required approximately 50 seconds to reach convergence on the solution, an acceptable time period considering the exploration of a wide variety of 540,000 different teams in the case of the men's baseball team. After analyzing the results, it has been confirmed that genetic algorithms constitute an effective approach to addressing problems of this nature. The algorithm has proven effective in forming teams with high balanced scores in both sports, reflecting a good adaptation to the required physical demands. The consistency in the performance of key players and the variability in physical abilities demonstrate the algorithm's ability to find optimal combinations within the established generation constraints.

4 Conclusions

After exhaustive analysis of the results derived from the tests executed on the genetic algorithm, it can be concluded that the teams formed by the algorithm exhibit acceptable quality and are generated in an optimal time interval, which implies a substantial saving of computing resources. This optimizes the work of coaches by facilitating the individual evaluation of players.

It is crucial to emphasize that, despite the quality and efficiency demonstrated by the algorithm, its implementation does not guarantee the success of the team formed. The sports environment involves multiple non-quantifiable variables, which are inherently dependent on individual circumstances.

The growing influence of artificial intelligence in various contemporary fields is undeniable, and genetic algorithms emerge as crucial tools for solving complex problems, as presented in this project. Their implementation is highly feasible thanks to their demonstrated efficiency in the use of computing resources and time management, positioning them as key elements at the forefront of technological solutions.

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