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Article

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Comparative analysis basketball shooting percentage using enhanced bio-inspired dwarf mongoose optimization algorithm with encircling foraging strategy

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Abstract Estimates from the international basketball federation suggest that globally, at least 450 million individuals are engaged in basketball sports. This paper an enhanced dwarf mongoose optimization algorithm with encircling foraging strategy (EDMOA) for comparative analysis basketball shooting percentage is proposed. Initially, it identifies shooting parameters-such as shooting distance, shooting velocity, shooting height, and angle-for general shooting scenarios, analyzing these parameters to provide scientifically sound shooting recommendations. Subsequently, it investigates the parameters affecting three-pointers and free throws, outlining feasible shooting strategies. It compares and analyzes the differences between three-pointer and free-throw shooting techniques while assessing the impact of distance on shooting outcomes. Finally, the study investigates shooting for tall players and short players, identifying distinct shooting parameters for both types of athletes and analyzing the differences in shooting approaches. The experimental results show that within reasonable ranges of other parameters, shooting three-pointer yields 87.09% increase in shooting accuracy compared to shooting two-pointers, while maintaining a shooting angle of approximately 52° results in an 86.30% increase in shooting accuracy. Leveraging the EDMOA, this paper addresses the above-mentioned issues. The EDMOA improves upon the limitations of the dwarf mongoose optimization algorithm (DMOA), which suffers from slow convergence and susceptibility to local optima, by introducing encircling foraging strategies and a survival-of-the-fittest population mindset. The outcomes of this study offer reference points for basketball coaches in designing training regimes for athletes. This research aims to provide scientifically grounded guidance for basketball player training, ultimately enhancing shooting percentage.

Keywords Dwarf mongoose optimization algorithm; encircling foraging strategy; basketball shooting percentage; comparative analysis; metaheuristic optimization

1 Introduction

Basketball, originating in 1891, has evolved into one of the three major ball sports, having gained significant global prominence [1]. In our country, basketball boasts a wide audience, ranking among the most popular sports [2]. It's a team sport governed by specific rules, combining individual skill and teamwork dynamics [3]. Despite being a team-oriented activity requiring coordinated efforts, an individual player's shooting accuracy significantly influences a team's ultimate success. Hence, systematic training plays a pivotal role in enhancing players' shooting percentage [4].

Shooting encompasses a series of intricate technical actions involving factors such as the shooting angle, height, and velocity of the basketball [5], making scientifically informed training imperative [6]. Traditional methods of improving shooting percentage accuracy experience. However, this approach remains highly subjective, with complex processes and poor accuracy. Difficulty in directly perceiving shooting angles, heights, and velocity hinders effective control over the ball's trajectory, resulting in lower shooting percentage for basketball players globally [7].

The General Secretary of Basketball Games emphasized the necessity of innovative training philosophies and enhancing athletes' competitive abilities in the new era, underscoring the sport's reliance on scientific training. The core of modern sports training emphasizes precision and efficiency. Providing accurate shooting strategies significantly enhances training outcomes and holds vital importance in enhancing athletes' competitive capabilities [8]. Hence, offering scientific guidance to enhance shooting accuracy becomes a crucial research direction [9].

Presently, some scholars offer shooting recommendations through numerical analysis by establishing parameter equations for shooting trajectories [7], [10-13]. However, numerical analysis methods can only solve simple trajectory equations, limiting the range of shooting solutions and making the solving process cumbersome. Others use MATLAB software to graph shooting trajectory equations [14-16], estimating feasible shooting angles and heights based on image analysis. Certain scholars combine shooting motion imagery and basketball trajectory equations for analysis [17], [18], utilizing image feature extraction to analyze shooting parameters. Nonetheless, traditional image analysis methods often fail to precisely represent changes in shooting angles during the shooting process, potentially leading to contrast deficiencies and prolonged processing times using existing intelligent visual decomposition techniques [19].

Furthermore, previous studies focus on individual or select parameters influencing shooting accuracy, disregarding the interconnectedness among shooting parameters. For instance, shooting height influences shooting angle and velocity, in turn, are affected by shooting distance [20].

Given the vibrant development of heuristic algorithms, applying these algorithms to resolve shooting parameters to enhance shooting percentage presents a novel research avenue. Leveraging heuristic algorithms allows for comprehensive considerations of shooting angles, velocities, heights, and distance to compensate for the limitations of previous studies .Hence, this paper aims to utilize heuristic algorithms to determine shooting angles, heights, velocities, and distance s to successful shots. This endeavor aids coaches in formulating scientifically sound training strategies for athletes, ultimately improving their shooting accuracy. This research pioneers a new frontier in enhancing basketball shooting accuracy, promising new breakthroughs and results.

The shooting percentage of free throws and three-pointers has been proven to be a crucial factor in ensuring expected outcomes across various levels of basketball competitions [21], [22]. Thus, this paper delves into the study of three-pointer and free throw shooting schemes, identifying leading parameters to successful shots and analyzing differences between these shooting methods. The formulation of shooting strategies for tall and short players has been a perennial issue for coaches. Hence, this study investigates shooting schemes tailored for tall and short players, providing comparative analyzes and scientifically grounded recommendations. Utilizing basketball trajectory equations considering air resistance and buoyancy, EDMOA is employed to determine accurate shooting parameters. DMOA is an effective swarm intelligence algorithm used for optimization problems [23], notable for its simplicity and minimal parameters but suffers from slow convergence and susceptibility to local optima [24].

The original DMOA simulates individual mongoose foraging behavior. However, research suggests that apart from solitary foraging, mongoose occasionally engage in group hunting. Therefore, drawing inspiration from the gray wolf optimization algorithm, this paper enhances the alpha group foraging stage of DMOA, introducing encircling foraging strategies to escape local optima. Incorporating survival-of-the-fittest principles, it eliminates the lowest 10% fitness individuals from the population, fostering new individuals through vertical and horizontal crossovers to expedite algorithm convergence. The proposed EDMOA algorithm aligns more realistically with the survival and development patterns of the dwarf mongoose population.

The main contributions of this paper are as follows:

(1) An enhanced dwarf mongoose optimization algorithm (EDMOA) is proposed.

(2) The EDMOA with multiple strategies to comparative analysis basketball shooting percentage.

(3) The outcomes of this study offer reference points for basketball coaches.

(4) We provided scientifically grounded guidance for basketball player training.

(5) The encircling foraging and survival-of-the-fittest population mindset into DMOA to better align with the developmental patterns of actual dwarf mongoose populations.

The remainder of this paper is organized as follows: Section 2 presents the literature review. Section 3 introduces the shooting model. Section 4 describes the construction of EDMOA. Section 5 presents the experimental results and discussions. Section 6 concludes this paper and outlines future research directions.

2 Related works

Several scholars have contributed to improving shooting accuracy through various methods. Brancazio et al. [25] conducted research on the trajectory equations for hollow balls, calculating the shooting velocity and angle ranges for shooting hollow balls. Wang et al. [12] analyzed shooting distance, height, and angle by combining shooting images and basketball trajectory equations, identifying correlations between shooting parameters. Wang et al. [7] investigated the relationship between shooting initial velocity and distance, exploring whether different shooting distances affect the standard deviation of shooting velocity. Changjan, A. et al. [11] utilized derivatives to solve shooting trajectory equations, providing numerical values for successful shooting parameters. Wang et al. [26] studied the impact of different shooting distances on shooting accuracy through biomechanical experiments and shooting images. Feng [10] conducted numerical analysis on basketball trajectory equations, deducing correlations between parameters for three-point shooting. Chen [14] performed numerical analysis on the trajectory equations for three-pointers, offering feasible ranges for shooting parameters. Dimitrije et al. [27] analyzed athletes' shooting images, studying kinematic differences among two-pointers, free throws, and three-pointers. Cabarkapa, et al. [28] investigated differences in shooting techniques between three-pointers and two -pointers by analyzing athletes' shooting images. Emilija, et al. [29]

researched shooting angles for forwards, guards, and centers, discovering that centers tend to have lower shooting angles compared to forwards and guards. Wang et al. [19] proposed an intelligent visual image decomposition method based on odd-value decomposition for basketball shooting angles, analyzing changes in shooting angles under different shooting conditions. Fan et al. [30] introduced a Squeeze Convolution Gating Attention (SCGA) deep learning model to recognize various sensor-fused basketball shooting postures. Zhao et al. [31] used Support Vector Machine (SVM) and Gaussian Mixture Model to identify shooting actions in basketball video images, applicable in enhancing teaching processes for basketball coaches and players. Fan et al. [5] designed a sensor-fused basketball shooting posture recognition system based on a convolution neural network. This system, employing a sensor fusion framework, collects basketball player posture data and uses a convolution neural network-based deep learning model for recognition. Liu et al. [3] applied convolution neural network technology to athlete training, recognizing athlete postures to assist coaches in decision-making and enhancing athletes' competitive abilities.

3 Basketball shooting model

3.1 Physical model

The motion of the basketball after it is shot adheres to Newton's Second Law and corresponds to projectile motion. The theoretical model, as depicted in Fig.1 is established. A global coordinate system, illustrated in Fig.1, is established with the center point of the hoop's vertical projection onto the ground as the coordinate origin. At the moment of shooting, the coordinates of the basketball's center are given by $(-x^*, y^*)$,the initial velocity is v_0 , the shooting angle is θ_0 , and the hoop's position is $(0, H)$, where $H = 3.05\text{m}$.

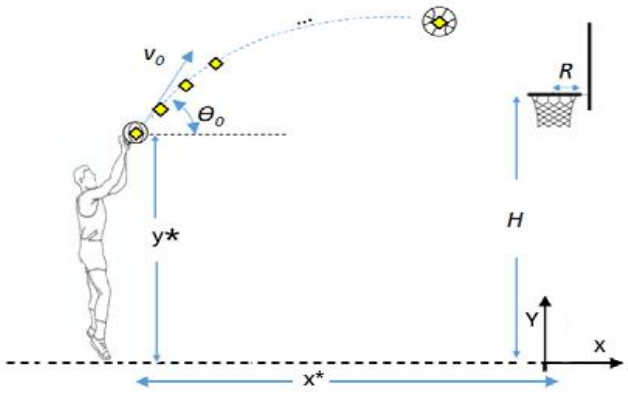


Fig. 1 Shooting model

3.2 Establishing the shooting trajectory equation

While in mid-air, the basketball experiences the forces of gravity, air buoyancy, and resistance. The shooting process can be viewed as the player releasing the basketball with an initial velocity v_0 and angle θ_0 guiding the ball through the hoop. The force equation of a basketball during flight is shown in Eq.(1).

$$m_t a = f_W + f_B + f_D \tag{1}$$

where $v = v_x i + v_y j$, $a = v_x i + v_y j$ are the velocity and acceleration of the ball, $f_W = -(m_a + m_b)gj$ are the gravity on the ball, $f_B = m_a gj$ are the buoyancy on the ball, m_b , m_a and m_t are the mass of the basketball, the mass of the air in the basketball, and the total mass of the basketball respectively. The resistance force experienced by the basketball is Eq. (2).

$$f_D = -\frac{\pi\rho D^2}{8} C_D V v \tag{2}$$

where D the diameter of the basketball is, $V = \sqrt{v_x^2 + v_y^2}$ is the velocity of the basketball, C_D is the drag coefficient. Improved approximate solutions involving drag are found using methods adopted in the external ballistics literature, where it is generally assumed that if the velocity is very high or the velocity range is small (the latter applies to basketballs), C_D can be accurately approximated as k/V , where k is a known constant. Define the ballistic coefficient as Eq.(3).

$$\beta = \frac{\pi\rho D^2 k}{8 m_t} \tag{3}$$

Establish basketball trajectory parameter equations such as Eq.(4) and Eq.(5).

$$x(t) = x_o + \frac{v_{xo}}{\beta}(1 - e^{-\beta t}) \tag{4}$$

$$y(t) = y_o + \left(\frac{v_{yo}}{\beta} + m' \frac{g}{\beta^2} \right)(1 - e^{-\beta t}) - m' \frac{g}{\beta} t \tag{5}$$

where $m' = m_b / m_t$, the final basketball trajectory equation is obtained by eliminating parameters of the basketball trajectory parameter equation, such as Eq.(6).

$$y^* - H + \left(\tan\theta_0 + \frac{m'g}{\beta v_0 \cos\theta_0} \right) x^* + m' \frac{g}{\beta^2} \ln\left[1 - \frac{\beta}{v_0 \cos\theta_0} x^* \right] = 0 \tag{6}$$

The symbols used in this model are explained in Table 1.

Table 1 Description of symbols

Symbol	Definition
H	Basket height
x^*	Distance from shooting point to basket
y^*	Shooting height
v_0	Initial velocity of shot
θ_0	Shooting angle
m_b	Quality of basketball
m_a	Air quality inside a basketball
m_t	Total mass of basketball
f_W	Gravity
f_B	Buoyancy
f_D	Air resistance
D	Basketball diameter
C_D	Air resistance coefficient
β	Ballistic coefficient

3.3 Problem description

The basketball is affected by gravity, air buoyancy and resistance when flying in the air. The shooting process can be regarded as the athlete standing in the shooting position $(-x^*, 0)$ with the initial shooting velocity v_0, shooting angle θ_0, shooting height y^* the shot is made so that the basketball goes through the basket. In summary, the problem of finding the parameters of a successful shot can be defined as Eq.(7).

$$f(y_*, x_*, v_0, \theta_0) = y_* - H + \left(\tan\theta_0 + \frac{m'g}{\beta v_0 \cos\theta_0} \right) x_* + m' \frac{g}{\beta^2} \ln\left[1 - \frac{\beta}{v_0 \cos\theta_0} x_* \right]$$

$$s.t. \begin{cases} 1.75m < y_* < 2.9m \\ 0.5m < x_* < 15m \\ 7.5m/s < v_0 < 11m/s \\ 30^o < \theta_0 < 85^o \end{cases} \tag{7}$$

4 Proposed EDMOA algorithm

This section delineates the algorithm aimed at addressing the challenge of determining parameters for successful basketball shots. Consider Eq.(7) as a multi-parameter optimization problem, this paper proposes EDMOA to tackle it. In this section, an initial presentation of the original DMOA is provided, followed by the proposition of enhancement strategies and a comprehensive exposition of EDMOA. Subsequently, an elaboration is offered on the utilization of EDMOA for determining optimal shooting parameters. Additionally, an analysis of the time complexity of EDMOA is presented.

4.1 DMOA

DMOA, proposed by Agushaka, Jeffrey O, and colleagues in 2022, is a population-based intelligent optimization algorithm. The algorithm's design emulates the semi-aquatic behavior and compensatory adaptive behavior of the mongoose population. Demonstrating robust global search capabilities, this algorithm involves optimization of a single parameter [32]. The population of civets is divided into three groups: Alpha, Alpha/Scouting, and Babysitter.

(1) ***Alpha Group***

Within the Alpha group, mongoose search for food to locate the optimal feeding position. Using the roulette wheel selection method based on Eq.(8), the algorithm identifies the leader of the Alpha group. Individual mongoose update their positions according to Eq.(9).

$$\alpha = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \tag{8}$$

$$X_{i+1} = X_i + ph_i * peep \tag{9}$$

In this context, $peep$ the simulation of the vocalization emitted by the female leader phi corresponds to a random number conforming to a normal distribution within the range of [-1,1]. Following each iteration, the sleeping mound undergoes updates as per Eq.(10), while the overall

quality of the sleeping mound is evaluated through Eq.(11). Subsequently, the algorithm transitions into a scouting phase, assessing the next food source or sleeping mound once the conditions for babysitter exchange are met.

$$sm_i = \frac{\left(fit_{i+1} - fit_i \right)}{\max\left\{ fit_{i+1}, fit_i \right\}} \tag{10}$$

$$\varphi = \frac{\sum_{i=1}^{n} sm_i}{n} \tag{11}$$

(2) ***Scouting Group***

The task of the Scouting group entails exploring habitats, specifically seeking the optimal sleeping mounds. Mongoose select sleeping mounds based on Eq.(12), where factors *M* as Eq.(13) and *CF* as Eq.(14).

$$X_{i+1} = \begin{cases} X_i - CF * phi * rand[X_i - M], & if\ \varphi_{i+1} > \varphi_i \\ X_i + CF * phi * rand[X_i - M], & otherwise \end{cases} \tag{12}$$

$$M = \frac{\sum_{i=1}^{n} X_i * sm_i}{X_i} \tag{13}$$

$$CF = \left(1 - \frac{iter}{MaX_{iter}} \right)^{\left(2\frac{iter}{Max_{iter}} \right)} \tag{14}$$

(3) ***The babysitters***

Once noon approaches, the foraging Alpha group of mongoose returns for babysitter exchange, and the position of the babysitter group are generated according to Eq.(15).

$$x_i = unifrnd(VarMin, VarMax, VarSize) \tag{15}$$

The DMOA pseudo-code is given in Algorithm 1.

Algorithm 1: DMOA.

1: **Input:** $peep, nPop, bs, L, nAlphaGroup$

2: Initialize the algorithm solutions, $Cbest$ and $Gbest$.

3: **while** ($iter < Maxiter$) **do**

4: Set alpha use Eq.(8)

5: Create new position use Eq.(9)

6: Calculate sleeping mound use Eq.(10)

7: Calculate average sleeping mound use Eq.(11)

8: Set time counter $C = C + 1$.

9: **if** $C > L$

10: Initialize the DMOA population use Eq.(15)

11: Set $C = 0$

12: **end if**

13: Update solutions position use Eq.(12)

14: $iter = iter + 1$

15: **end while**

16: **Output:** Return the most effective solution x .

4.2 EDMOA

This section provides an introduction to the proposed EDMOA algorithm, primarily addressing the issues of slow convergence and susceptibility to local optima present in the original algorithm.

4.2.1 Encircling foraging strategies

Studying the behavioral traits of mongoose revealed that besides individual foraging for small prey, they occasionally engage in group ambush hunting for larger prey. To better mirror mongoose behavior, this study proposes an enhancement technique called Encircling foraging strategies, drawing inspiration from the Grey Wolf Optimization (GWO) algorithm. Initially, three optimal mongoose, P_α , P_β and P_δ are selected. Distances between individual mongoose and among them are computed as Eq.(16), Eq.(17) and Eq.(18).

$$d_\alpha = | c_1 \cdot P_\alpha - x_i | \tag{16}$$

$$d_\beta = | c_2 \cdot P_\beta - x_i | \tag{16}$$

$$d_\delta = | c_3 \cdot P_\delta - x_i | \tag{17}$$

where c_1, c_2 and c_3 is random numbers within the range of [0,1] are used to randomly select three non-optimal mongoose, P_1, P_2 and P_3 from the remaining $n-3$ individuals.

These selected mongooses undergo computations as per Eq.(18), Eq.(19) and Eq.(20)

$$P_1 = \phi \cdot P_{r1} - r \cdot (d_\alpha) \tag{18}$$

$$P_2 = \phi \cdot P_{r2} - r \cdot (d_\beta) \tag{19}$$

$$P_3 = \phi \cdot P_{r3} - r \cdot (d_\delta) \tag{20}$$

where r_1, r_2 and r_3 is random numbers within the range of [0,1], r is random numbers within the range of [-1,1], $\phi = e^{-0.05*t}$.

The mongoose individuals are updated according to Eq.(22).

$$x_{i+1} = \frac{P_1 + P_2 + P_3}{3} \tag{21}$$

4.2.2 Survival-of-the-fittest

To better emulate the survival dynamics of mongoose individuals in their natural environment, the concept of individual survival of the fittest is introduced. This involves eliminating the lowest 10% of individuals based on their fitness ranking within the population. To replenish the population, a crisscross technique, termed longitudinal and transverse crossover, is employed. This strategy ensures that individuals produced through this crossover undergo both longitudinal and transverse exchanges. This approach aids in breaking free from local optima within the population [33]. The longitudinal crossover for individuals is described by Eq.(23), while the transverse crossover is defined by Eq.(24).

$$\begin{aligned} x_{i1+1} &= r_1 * x_{i1} + (1 - r_1) * x_{i2} + c_1 * (x_{i1} - x_{i2}) \\ x_{i2+1} &= r_2 * x_{i2} + (1 - r_2) * x_{i2} + c_2 * (x_{i2} - x_{i1}) \end{aligned} \tag{22}$$

$$x_{ij1+1} = r * x_{ij1} + (1 - r) * x_{ij2} \tag{23}$$

The improved algorithm's performance was tested on the single-objective CEC2022 benchmark functions. The population size was set to 50 individuals, iterated independently for 500 cycles, while maintaining consistent parameters except for this variation. Performance evaluation was conducted using the F7 function in dimensions of 5, 10, 15, and 20 for both DMOA and EDMOA. The results of these tests are shown in Fig.2, Fig.3, Fig.4, and Fig.5. Observing Fig. 2, Fig.3, Fig.4, and Fig.5 reveals the consistent superiority of EDMOA over DMOA across both low and high dimensions. EDMOA demonstrates accelerated convergence compared to DMOA, aiding in escaping local optima.

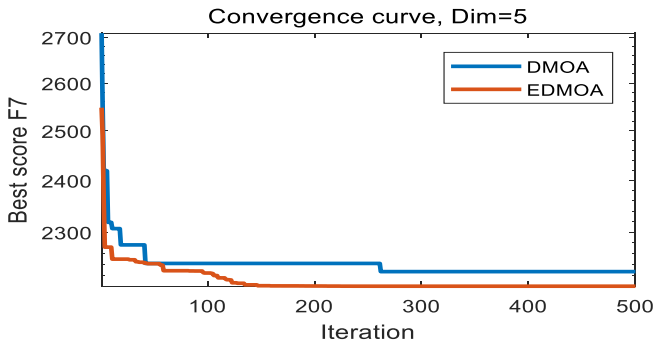


Fig. 2 5-Dimensional Test of F7 Function

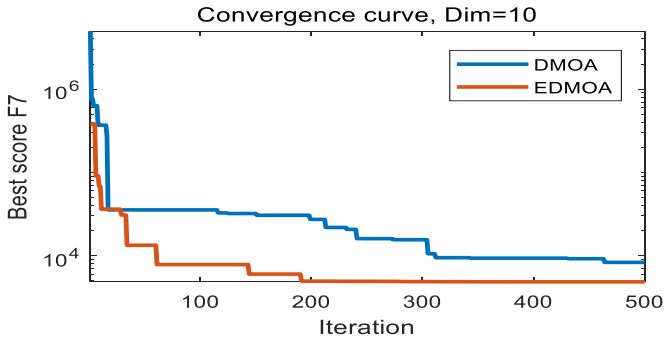


Fig. 3 10-Dimensional Test of F7 Function

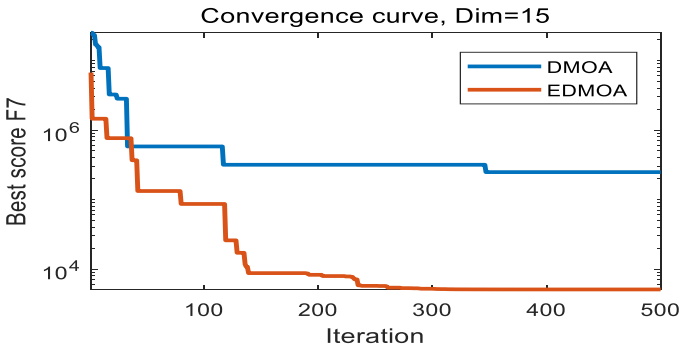


Fig.4 15-Dimensional Test of F7 Function

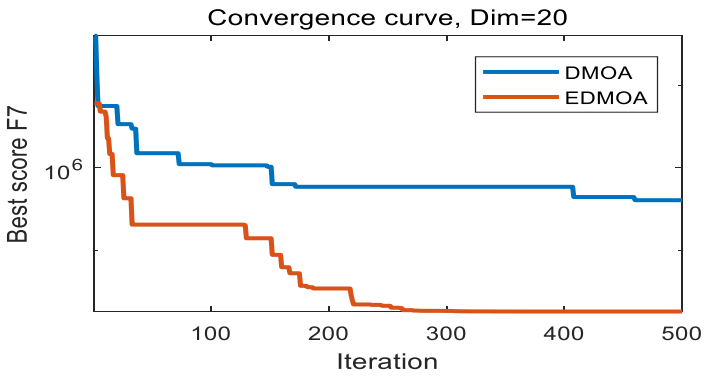


Fig. 5 20-Dimensional Test of F7 Function

The pseudo-code of the EDMOA algorithm is as follows Algorithm 2

Algorithm 2. EDMOA

1: **Input:** Set the conditions and solutions for the algorithm.

2: Initialize the algorithm parameters and solutions.

3: Set $nAlpha = nScout = 90\% \times nPop$, $nBabysitter = nPop - nAlpha$

4: **while** ($iter < Max_{iter}$) **do**

5： Select the bottom 10% individuals ranked by fitness

6: **if** rand > 0.5

7: Update the solutions' positions using Eq.(22)

8: **else**

9: Update the solutions' positions using Eq.(23).

10: **end if**

11: Set alpha use Eq. (8)

12: **if** rand > 0.7

13: Update the solutions' positions using Eq.(9)

14: **else**

15: Update the solutions' positions using Eq.(21)

16: **end if**

17: Calculate sleeping mound use Eq.(10)

18: Calculate average sleeping mound use Eq.(11)

19: Set time counter $C = C+1$

20: **if** $C < L$

21: Update the solutions' positions using Eq.(15)

22: **end if**

23: Update solutions position use Eq.(12)

24: $iter = iter + 1$

25: **end while**

26: **Output:** Return the most effective solution (*x*).

The EDMOA flow chart is shown in Fig.6

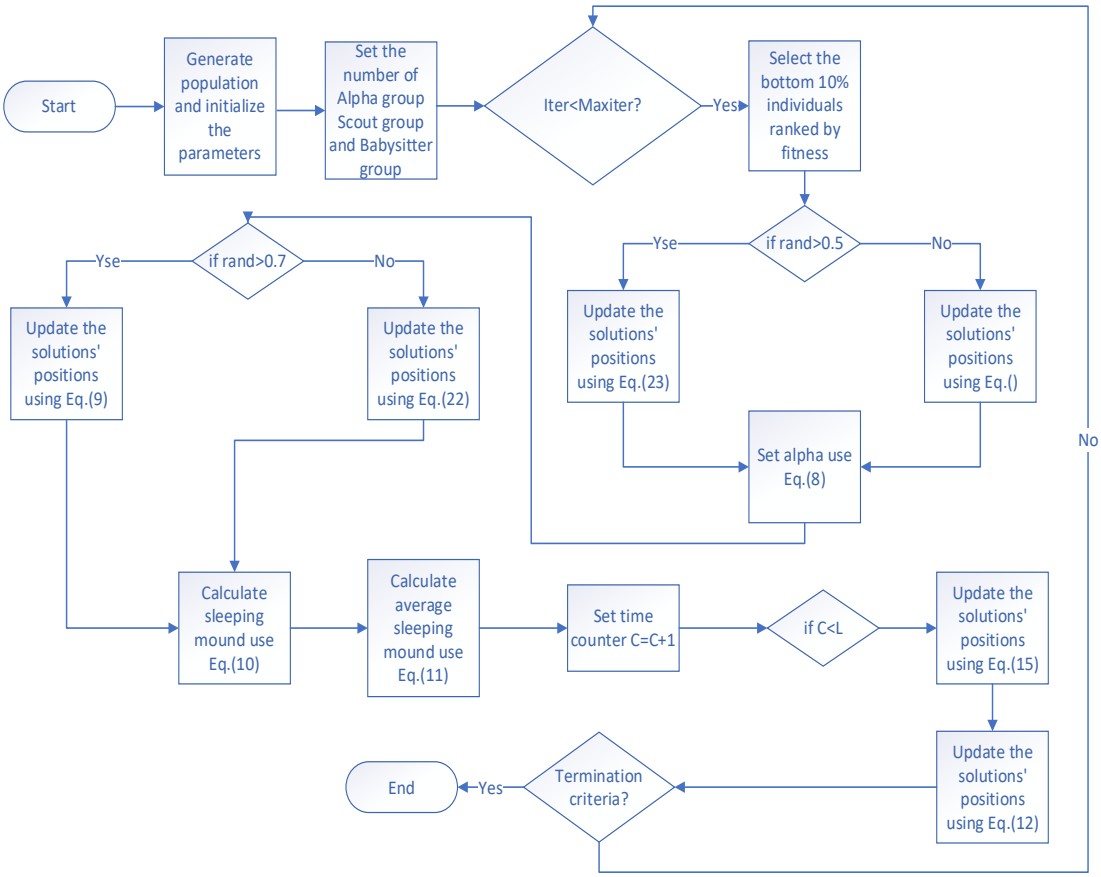


Fig. 6 Flowchart of EDMOA algorithm

4.3 Applied EDMOA for finding basketball shooting parameters

The trajectory model for basketball shots, as depicted in Fig.1, involves a player positioned at $(-x^*,0)$ with initial shooting velocity v_0, shooting angle θ_0, and shooting height y^*. Employing EDMOA to determine the player's shooting distance , initial velocity, shooting angle, and shooting height to achieve a successful basketball shot follows these steps:

Step 1. Initialize the Mongoose population X , X as defined in Eq.(24), where each individual $x_i = [x^*_i, y^*_i, v_{0_i}, \theta_{0_i}]$.

$$X = \begin{bmatrix} x_1^* & y_1^* & v_{0_1} & \theta_{0_1} \\ x_2^* & y_2^* & v_{0_2} & \theta_{0_2} \\ \cdots & \cdots & \cdots & \cdots \\ x_n^* & y_n^* & v_{0_n} & \theta_{0_n} \end{bmatrix} \tag{24}$$

Step 2. Employ EDMOA for iterative updates on the mongoose population, aiming to identify the shooting distance, initial velocity, shooting angle, and shooting height that result in successful basketball shots.

4.4 EDMOA time complexity

The time complexity of EDMOA primarily relies on individual initialization and updates, encompassing function fitness calculations, population selection, female leader selection, mound evaluation, and computation of movement vectors and step sizes. Consequently, the time complexity of EDMOA is given by $O(Maxiter \times d \times \alpha \times sm \times M \times step \times n + CFE \times n)$.Where represents the population size, d signifies the problem's dimensionality, and CFE denotes the computational expense of the function evaluation. Therefore, the time complexity of EDMOA is $MAX(N^2 \log^{M-2} N, N^2 M) + Maxiter \times d \times \alpha \times sm \times M \times step \times n + CFE \times n$.

5 Experiment results and discussion

This study utilizes EDMOA to determine the shooting parameters for successful basketball shots, with the hoop height set at 3.05 meters. The experiment comprises three main sections: Firstly, addressing general shooting scenarios to identify viable shooting parameters-player's shooting distance, angle, initial velocity, and height and providing shooting recommendations. Secondly, determining the three-point and free-throw shooting parameters, analyzing the differences and similarities between these shooting scenarios. The three-point shooting distance is set at a distance of 6.75 meters from the hoop, while the free-throw shooting distance is at 4.57 meters. Analyzed the similarities and differences in parameters and shooting strategies, provide recommendations for three-point and free-throw shooting. Lastly, analyze the differences in shooting strategies between tall and short players. Setting the shooting height for tall players at [2.3m-2.9m], and for short players at [1.9m-2.2m], and examining the related parameters and feasible shooting strategies. Tailoring shooting recommendations specifically for tall and short players. This experiment aims to offer reference points for coaches to devise suitable training programs, provide scientifically effective advice and guidance for athletes' training, enhance their shooting accuracy, and contribute to the field of sports.

Table 2 outlines the experimental settings, while Table 3 details the EDMOA parameters. Table 4 presents the shooting experiment parameters.

Table 2 System Performance

Experimental environment	Setting
Hardware	
CPU	Intel Core(TM) i5-4210U
Frequency	2.4 GHz
RAM	4 GB
Hard drive	500 GB

Software	
Operating system	Windows 10
Language	MATLAB R2017b

Table 3 Algorithm Parameter Settings

Algorithms	Parameter	Value
EMODMOA	Peep	2
	Population size	500

Table 4 Experimental Parameter Settings

Notation	Values
H	$3.05m$
m_b	$0.624kg$
m_t	$0.645kg$
D	$0.241m$

5.1 Shooting strategies

Using EDMOA to explore combinations of shooting parameters resulting in successful shots, this experiment involves independent runs of EDMOA for 10 iterations, each comprising 500 algorithmic cycles. The convergence plot of algorithmic iterations is shown in Fig.7. A total of 590 distinct combinations resulting in successful shots were collected. Statistical analysis was conducted on these successful shot parameters to provide shooting recommendations.

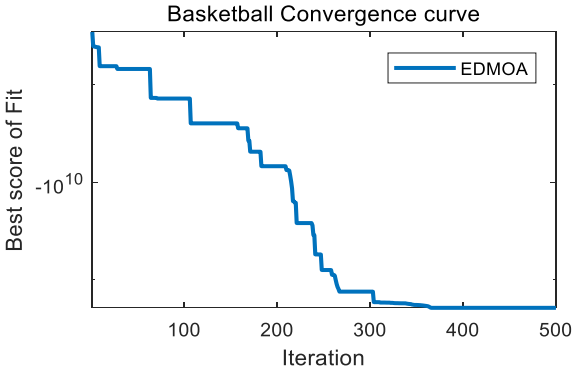


Fig.7 Convergence diagram of the algorithm

The parameters for successful and unsuccessful shots underwent independent sample Mann-Whitney U tests. Findings revealed significant differences in the data distribution between successful and unsuccessful shots for shooting angle (p=0.002), initial velocity (p=0.000),

shooting distance (p =0.000), and shooting height (p=0.000). This indicates significant influences of shooting angle, initial velocity, shooting distance, and shooting height on the basketball's ability to go in, underscoring the significance of the parameters investigated in this experiment.

Descriptive statistics were performed on the collected 590 successful shooting parameters, detailed in Table 5. Observing the mean, median, and standard deviation of each parameter, it is noted that the standard deviation for shooting angle is considerably large, indicating dispersed data. Conversely, the standard deviations for the other parameters are small, signifying that successful values are concentrated around their means.

Table 5 Statistical description of shooting parameters

	Shoot angle	Shoot velocity	Shoot distance	Shot height
Aggregate	590	590	590	590
Mean	50.44	8.75	11.51	2.29
Median	51.85	8.56	11.82	2.30
Std	9.40	0.88	2.23	0.31

The correlation analysis of shooting parameters is shown in Table 6. Observing Table 6, it reveals a negative correlation between shooting angle and shooting velocity, shooting distance, as well as shooting height. Meanwhile, shooting velocity shows a positive correlation with shooting distance and a negative correlation with shooting height. When shooting from a longer distance, there's an inclination to increase shooting velocity while decreasing shooting height and shooting angle.

In [12], an analysis combining shooting imagery and basketball trajectory models examines shooting distance, shooting height, and shooting angle, concluding a positive correlation between shooting distance and shooting velocity, and a negative correlation between shooting distance and shooting angle. In [7], employing shooting imagery and basketball trajectory equations, explores shooting velocity, shooting height, and shooting angle, establishing a negative correlation between shooting height and shooting angle as well as a negative correlation with shooting velocity. In [11] applies derivative methods to the basketball trajectory equation, analyzing shooting velocity, shooting height, and shooting angle, and confirms a negative correlation between shooting height and shooting angle.

These findings align with the conclusions drawn in this paper. Furthermore, it's evident that previous research primarily focused on analyzing three parameters-shooting height, shooting angle,

and shooting velocity-in shooting studies. However, shooting is a holistic process where each parameter can influence the shooting outcome. The approach used in this experiment allows for a comprehensive analysis of all four parameters.

Table 6 Correlation statistics of shooting parameters

		Shoot angle	Shoot velocity	Shoot distance	Shot height
Shoot Angle	correlation coefficient	1.000	-0.344	-0.297	-0.321
	Sig. (bobtail)	---	0.008	0.014	0.006
	N	590	590	590	590
Shoot Velocity	correlation coefficient	-0.344	1.000	0.179	-0.296
	Sig. (bobtail)	0.008	---	0.047	0.000
	N	590	590	590	590
Shoot Distance	correlation coefficient	-0.297	0.179	1.000	0.125
	Sig. (bobtail)	0.014	0.047	---	0.001
	N	590	590	590	590
Shot Height	correlation coefficient	-0.321	-0.296	0.125	1.000
	Sig. (bobtail)	0.006	0.000	0.001	---
	N	590	590	590	590

Scatter plots depicting shooting angle, initial shooting velocity, and shooting distance are shown in Fig.8. Upon observation, it is apparent from the scatter plots that nearly all successful shots have an initial shooting velocity below 8.5m/s, with the highest probability of scoring occurring at velocity below this threshold. The shooting angles leading to successful shots are concentrated around 52.5°. When shooting from beyond the three-point line, the probability of scoring increases with shooting angles of either 52.5° or 57° and initial shooting velocity between 7.6m/s and 8.4m/s, while a shooting angle of 15° also presents a possibility of scoring. In the case of two-point field goals, successful shots predominantly occur at a shooting angle of 52.5° and a velocity of 7.6m/s.

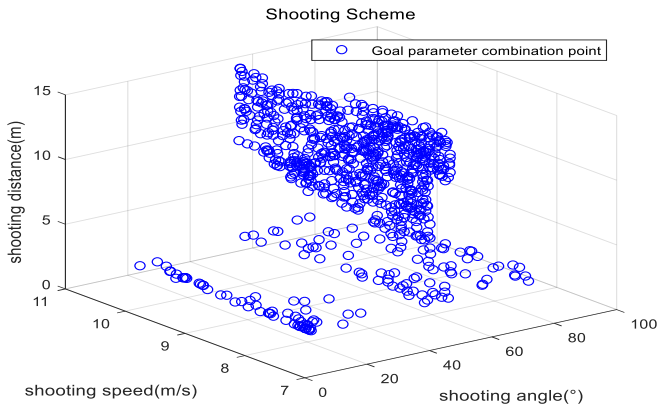


Fig. 8 Shooting velocity angle distance

Scatter plots depicting shooting distance, shooting height, and initial shooting velocity are shown in Fig.9. Observing the scatter plots, it is evident that when shooting from beyond the three-point line, the probability of scoring increases significantly with a velocity of approximately 8.5 m/s and a shooting height between 2.4-2.8m. Within the two-point shooting area, the likelihood of scoring is higher at velocity around 7.8m/s and shooting heights between 1.8-2m.

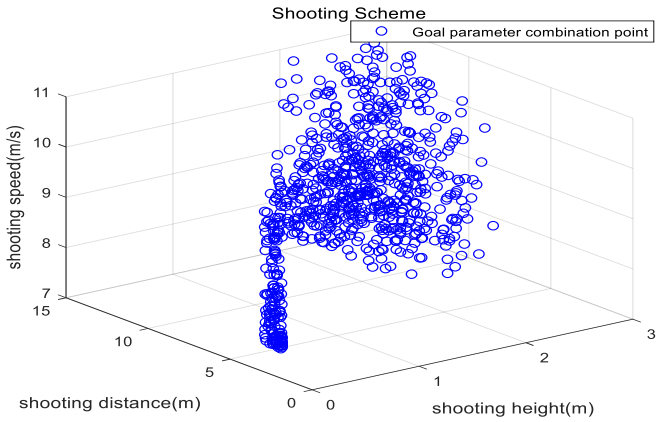


Fig. 9 Shooting distance height velocity

Scatter plots of shooting distance, shooting height, and shooting angle are shown in Fig.10. Observing the shooting scatter plots reveals that when shooting from beyond the three-point line, shooting at an angle of 52.5° with a shooting height between 1.9m and 2.2m maximizes the probability of scoring. For two-point shots, shooting at a 52.5° angle, the optimal shooting height for a higher scoring probability is around 1.8m or between 2.2m and 2.4m.

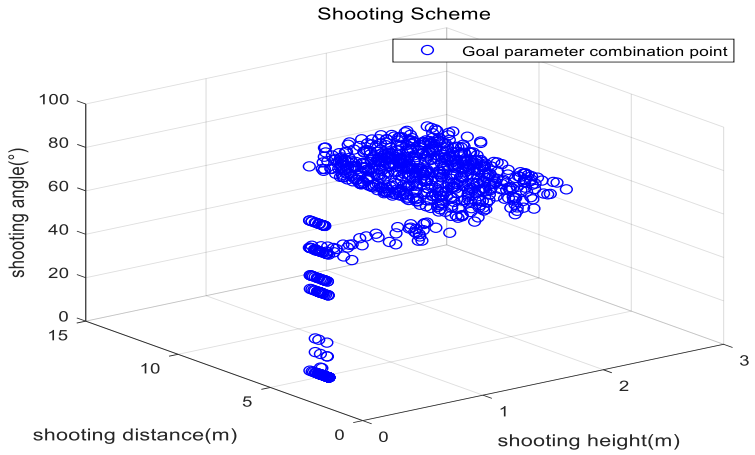


Fig. 10 Shooting distance height angle

Analyzing the scatter plots across various parameters, shooting from beyond the three-point line shows a higher probability of scoring when shooting at a 52.5° angle with a shooting velocity between 7.6-8.4m/s, and the shooting height ranging between 1.9-2.2 m or 2.4-2.8m. Shooting at

around 15° angle with a velocity of approximately 7.6m/s, and a height of about 2.6m or 1.8m results in a higher probability of scoring. For two-point shots, shooting at a 52.5° angle with a velocity of 7.8m/s, and a height between 1.8-2m or 2.2-2.4m results in a higher probability of scoring.

In [34], using numerical analysis based on the shooting trajectory equation, suggests optimal shooting parameters. For shots beyond the three-point line, the best release height is between 2.4-2.8m, the optimal shooting angle is 50.4°-51.6° , and the recommended shooting velocity is between 7.90-8.47m/s. For two-point shots, the suggested release height is between 1.9-2.25m, with an optimal shooting angle of 51.4°-52.6°, and a recommended shooting velocity between 7.59-8.21m/s. These findings corroborate the experimental results obtained in this study.

In [7] presents four sets of shooting parameters derived from combining shooting imagery and basketball trajectory equations. In [26], through biomechanical experiments and shooting imagery, proposes three feasible shooting strategies, as detailed in Table 7, all of which fall within the feasible range determined by the scatter plots in this experiment. Utilizing EDMOA with a convergence precision of 1×10^{-17}, 73 distinct feasible shooting strategies were found in a single experiment, are shown in **Appendix Table A.1** shown cased of the discovered shooting parameter values capable of scoring.

Table 7 Shooting programmer from the literature

Ref.s	Shoot angle	Shoot velocity	Shoot distance	Shot height
[7]	52.6	7.67	4.60	1.8
[7]	52.0	7.59	4.60	1.9
[7]	51.4	7.51	4.60	2.0
[7]	51.0	7.43	4.60	2.1
[26]	52.16	7.21	4.06	2.50
[26]	52.67	7.58	5.72	2.56
[26]	51.40	8.10	6.46	2.60

In [35], [36] have indicated that with the evolution of the game, NBA players tend to favor shooting from long distances, leading to a noticeable increase in the probability of scoring from such distances. This preference for long-range shooting stems from the potential for higher scoring opportunities. However, it is noted that long-range shooting yields the lowest shooting percentage among various shooting zones (under the basket, within the free-throw line, between the three-point line and free-throw line). Nonetheless, this study has identified numerous successful long-range shooting strategies, offering guidance for player training to enhance their accuracy in

long-range shooting and secure higher scores in games.

In [37], [38] have highlighted that several basketball stars like Stephen Curry, Kevin Durant, James Harden, LeBron James, John Wall, Ryan Anderson, Nikola Mirotic, among others, demonstrate a strong inclination toward three-point shooting, commonly associated with long-distance attempts.

Numerous studies have proposed 52° as the optimal shooting angle in basketball. The feasible shooting angles identified in this experiment are predominantly clustered around 52°, yet there were also discovered shooting strategies that resulted in successful shots at angles near 57° or around 15° .

5.2 Three-Pointers vs. Free Throw

To explore shooting strategies for three-pointers and free throws, EDMOA was run independently for 10 iterations, with each iteration comprising 500 algorithmic steps. The convergence plots for the algorithm are shown in Fig.11 and Fig.12. A total of 500 unique successful shooting parameter sets were gathered for each scenario. Statistical analyses were performed on these successful shooting parameters to provide tailored shooting recommendations for both three-pointers and free throws, thereby analyzing the differences and similarities between these shooting schemes.

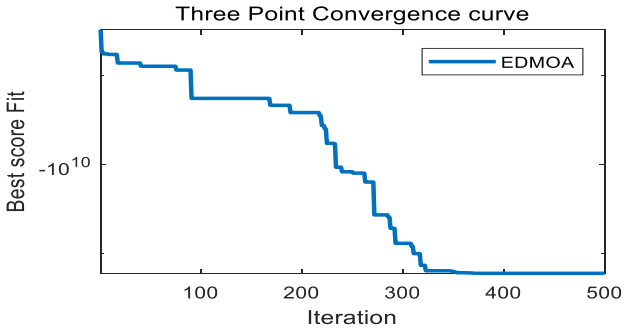


Fig.11 Iterative convergence diagram

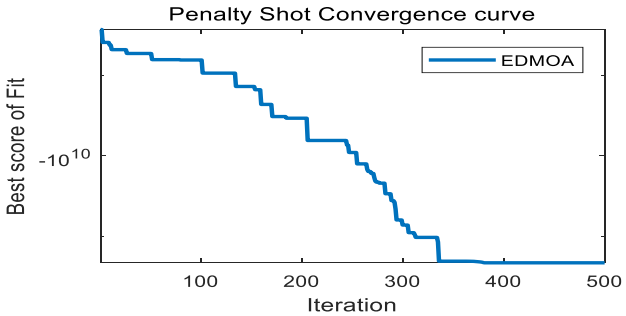


Fig.12 Iterative convergence diagram

Performing separate correlation tests on the shooting parameters for three-pointers and free throws yielded the results are shown in Tables 8-9. For three-pointers, the shooting velocity positively correlates with the shooting angle, while demonstrating a negative correlation with shooting height. Additionally, a negative correlation exists between the shooting height and angle for three-pointers. As for free throws, the shooting angle shows a negative correlation with velocity and height, whereas the velocity and height demonstrate a negative relationship.

Literature [14] conducted a numerical analysis of basketball trajectory equations, concluding a negative correlation between three-point shooting angles and height, as well as a negative correlation between the shooting velocity and heights for both three-pointers and free throws. Similarly, research [16], employing MATLAB software, illustrated a negative correlation between the shooting velocity and height for free throws. These findings align with the outcomes derived from this study.

Table 8 Three-point Shooting Parameter Correlations

		Three-point Shoot angle	Three-point Shoot velocity	Three-point Shot height
Three-point Shoot angle	correlation coefficient	1.000	0.111	-0.114
	Sig. (bobtail)	---	0.001	0.006
	N	500	500	500
Three-point Shoot velocity	correlation coefficient	0.111	1.000	-0.237
	Sig. (bobtail)	0.001	---	0.000
	N	500	500	500
Three-point Shot height	correlation coefficient	-0.114	-0.237	1.000
	Sig. (bobtail)	0.006	0.000	---
	N	500	500	500

Table 9 Free Throw Shooting Parameter Correlations

		Free Throw Shoot angle	Free Throw Shoot velocity	Free Throw Shot height
Free Throw Shoot angle	correlation coefficient	1.000	-0.585	-0.512
	Sig. (bobtail)	---	0.000	0.000
	N	500	500	500
Free Throw Shoot velocity	correlation coefficient	-0.585	1.000	-0.645
	Sig. (bobtail)	0.000	---	0.006
	N	500	500	500
Free Throw Shot height	correlation coefficient	-0.512	-0.645	1.000
	Sig. (bobtail)	0.000	0.000	---
	N	500	500	500

Respective scatter plots were generated for three-pointers and free throws, showing the shooting angles, velocity, and heights (refer to Fig.13 and Fig.14). Observing these scatter plots, for three-pointers, a shooting angle around 14.5°, with shooting velocity between 7.5 m/s and 8.1 m/s, coupled with a shooting height between 2.2 m and 2.4 m, demonstrate a higher success rate. Additionally, shooting angles of 51° or 58°, shooting velocity from 7.7 m/s to 8.4 m/s, and a shooting height around 2.2 m show a higher probability of scoring.

For free throws, an angle around 14°, shooting velocity between 7.3 m/s and 8 m/s, and a shooting height between 1.95 m and 2.2 m exhibit a higher shooting success rate. Similarly, shooting angles of 51° or 58° , shooting velocity between 7.5 m/s and 8.3 m/s, coupled with a shooting height around 2.1 m, demonstrate a higher likelihood of scoring.

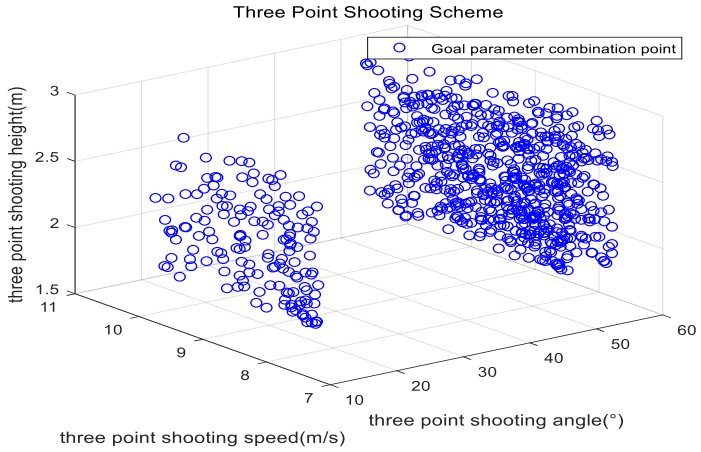


Fig.13 Three-point scoring programmer

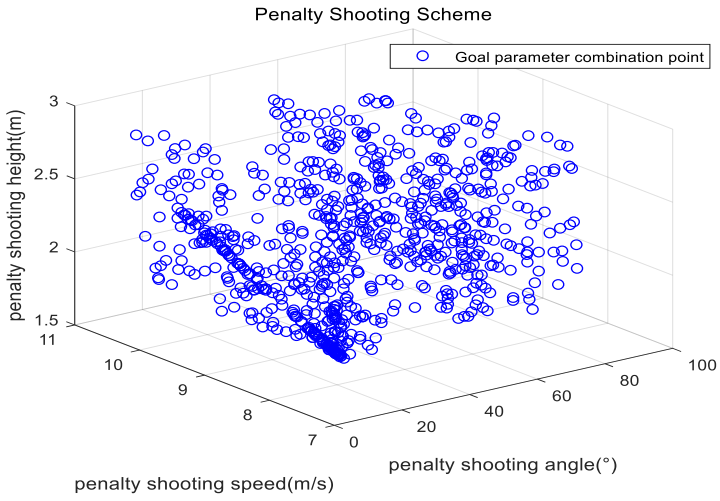


Fig.14 Free throw scoring programmer

For three-pointers, literatures [10], [39] conducted numerical analysis of the basketball trajectory equation, providing a set of feasible shooting parameters, detailed in Table 10.

Reference [14] analyzed the basketball trajectory equation, finding that with shooting heights ranging from 1.7m to 3m, the optimal shooting velocity lies between 7.85m/s and 8.71m/s, at an angle of 52°—aligning with the shooting recommendations derived from observing the scatter plots in this experiment. Using EDMOA, 58 distinct successful shooting parameter combinations for three-pointers were identified with a convergence precision of 1×10^{-17}, are shown in **Appendix Table A.2**.

Regarding free throws, literature [20] conducted numerical analysis of the basketball trajectory, determining that at a shooting height of 2.25m, the optimal shooting angle is 52°, with shooting velocity ranging from 7.5m/s to 8m/s, providing two sets of viable shooting parameter combinations. Additionally, literature [14] analyzed the basketball trajectory equation, revealing that at a shooting height of 2m, the ideal shooting angle is 52°, with shooting velocity between 7.6m/s and 8.5m/s. Furthermore, utilizing MATLAB software, literature [16], [40] illustrated the basketball trajectory equation, presenting two viable solutions and one feasible solution, respectively. EDMOA identified 42 distinct feasible solutions for free throws with a convergence precision of 1×10^{-16}, are shown in **Appendix Table A.3**.

Table 10 Viable scoring options for three-pointers and free throws

Ref.s	Shoot angle	Shoot velocity	Shoot distance	Shot height
[10]	51.63	8.35	6.75	2.25
[39]	51.87	7.73	6.75	2.36
[20]	52.8	7.79	4.57	2.25
[20]	57.8	7.91	4.57	2.25
[16]	52.8	7.69	4.57	2.20
[16]	58.8	7.89	4.57	2.20
[40]	51.3	7.68	4.57	2.10

Independent sample Mann-Whitney U tests were conducted on the parameter data for three-pointers and free throws, revealing shooting angles with p=0.002, initial velocity with p=0.162, and shooting heights with p=0.010. This suggests a marked disparity in the data distribution for successful shooting angles and heights between three-pointers and free throws, while the distribution of velocity data shows minimal variation. Descriptive statistics for three-pointers and free throws were computed, as presented in Table 11. Analysis of Table 11 indicates that the mean and median angles for three-pointers are slightly lower than those for free throws, while the mean and median heights for three-pointers are slightly higher than those for free throws. These findings align with literatures [27], [41], confirming that three -point shooting

angles tend to be marginally lower and the shooting heights slightly higher compared to free throws. Fig.15 demonstrated the similarities and differences in shooting parameters between three-pointers and free throws.

Table 11 Descriptive Statistics for Three-Point and Free Throw Shooting

	Three-point angle	Three-point velocity	Three-Point height	Free Throw angle	Free Throw velocity	Free Throw height
Aggregate	500	500	500	500	500	500
Mean	46.45	8.81	2.46	49.46	8.73	2.26
Median	51.84	8.71	2.48	52.84	8.61	2.24
Std	7.69	0.26	0.18	25.01	0.28	0.19

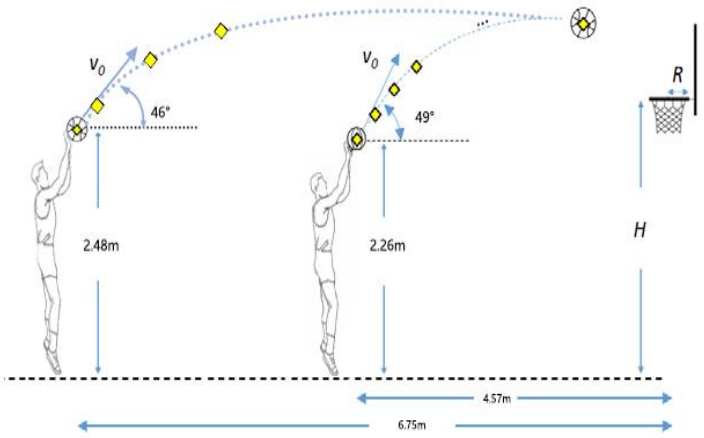


Fig. 15 Three-point shooting vs. Free throw shooting

5.3 Tall Basketball Players vs. Short Basketball Players

In studying the shooting strategies of tall and short basketball players, EDMOA was run independently 10 times, with each instance involving 500 algorithm iterations. The convergence plots for these iterations are shown in Fig.16 and Fig.17. A total of 500 distinct successful shooting parameter sets were collected, subjected to statistical analysis to derive shooting recommendations for tall and short players, and to delineate the differences and similarities in their shooting strategies.

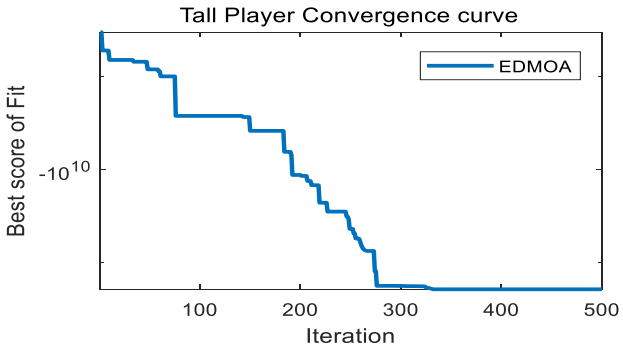


Fig. 16 Iterative convergence diagram

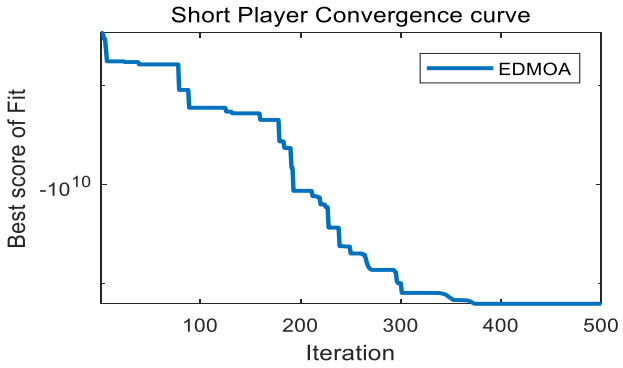


Fig. 17 Iterative convergence diagram

Conducting a correlation analysis on the shooting parameters of tall and short basketball players, the test results are outlined in Tables 12-13. It was observed that there exists a negative correlation between the shooting angle and both the shooting velocity and distance for both tall and short players. Additionally, there is a negative correlation between the shooting velocity and distance for both groups.

Table 12 Correlation of Shooting Parameters for Tall Players

		Tall Players Shoot angle	Tall Players Shoot velocity	Tall Players Shoot distance
Tall Players Shoot angle	correlation coefficient	1.000	-0.117	-0.112
	Sig. (bobtail)	---	0.000	0.002
	N	500	500	500
Tall Players Shoot velocity	correlation coefficient	-0.117	1.000	-0.070
	Sig. (bobtail)	0.000	---	0.044
	N	500	500	500
Tall Players Shoot distance	correlation coefficient	-0.112	-0.070	1.000
	Sig. (bobtail)	0.002	0.044	---
	N	500	500	500

Table 13 Correlation of Shooting Parameters for Short Players

		Short Players Shoot angle	Short Players Shoot velocity	Short Players Shoot distance
Short Players Shoot angle	correlation coefficient	1.000	-0.152	-0.119
	Sig. (bobtail)	---	0.000	0.003
	N	500	500	500
Short Players Shoot velocity	correlation coefficient	-0.152	1.000	-0.091
	Sig. (bobtail)	0.000	---	0.045
	N	500	500	500
Short Players Shoot distance	correlation coefficient	-0.119	-0.091	1.000
	Sig. (bobtail)	0.003	0.045	---
	N	500	500	500

Creating scatter plots for the shooting angle, velocity, and distance of shorter basketball players, the results are depicted in Fig.18. Observing the scatter plot, it is noted that shooting from beyond the three-point line, there's a higher probability of scoring with a shooting angle around 52° and a velocity of 8m/s. Additionally, shooting at 13° or 57° with velocities between 7.6 m/s and 8m/s also presents a chance of scoring. For two-point shots, a shooting angle of around 52° with velocities between 8 m/s and 9.5m/s shows potential for scoring. Using EDMOA to explore the shooting parameters for shorter players, 62 distinct feasible solutions were obtained with a convergence precision of 1×10^{-17}, are shown in **Appendix Table A.4**.

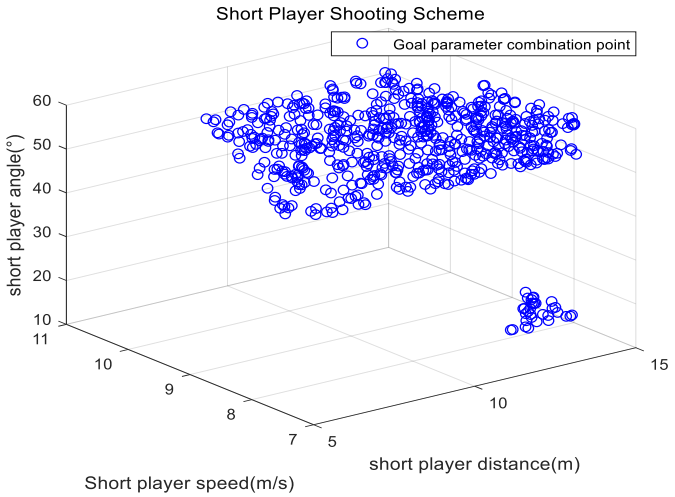


Fig. 18 Short players' goal-scoring schemes

Creating scatter plots for taller basketball players based on shooting angle, velocity, and distance resulted in Fig.19. Observing the scatter plot reveals that shooting beyond the three-point line shows a higher probability of scoring with a shooting angle around 52° and velocities ranging between 7.6m/s and 8.5m/s. Additionally, shooting at a 14° with velocities between 7.8m/s and 8.3m/s or at a 57° with velocities between 7.6m/s and 8.5m/ s also displays potential for scoring. For two-point shots, there's a chance of scoring with a shooting angle of 52° and velocities below 8m/s. EDMOA exploration for the shooting parameters of taller players discovered 67 distinct feasible solutions with a convergence precision of 1×10^{-17}, are shown in Appendix Table A.5 shown the shooting parameters for taller players obtained in this experiment.

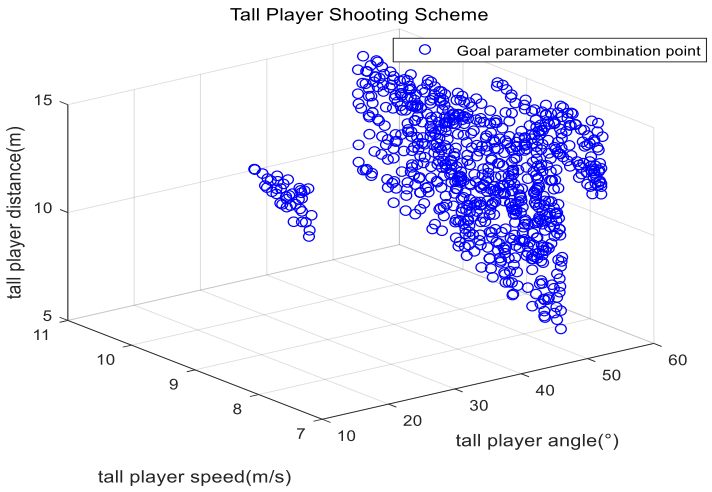


Fig. 19 Tall players' goal-scoring schemes

The independent-sample Mann-Whitney U test was conducted on shooting parameters for tall and short basketball players, revealing the following *p*-values: shooting angle p=0.752, initial shooting velocity p=0.020, shooting distance p=0.241. This signifies that only the distribution of shooting velocity significantly differs among players of different heights. Descriptive statistics were computed for shooting parameters of tall and short players, presented in Table 14. Upon observing the mean, median, and standard deviation of various parameters for tall and short players, it's evident that the mean and median shooting angles for both groups show minimal disparity. The mean initial shooting velocity for tall players slightly falls below that of shorter players, aligning with the conclusion derived in [42]. Additionally, the shooting distance for tall players is marginally longer than that for shorter players.

Table 14 Descriptive statistics of goal scoring parameters for tall and short players

	Tall player shoot angle	Tall player shoot velocity	Tall player shoot distance	Short player shoot angle	Short player shoot velocity	Short player shoot distance
Aggregate	500	500	500	500	500	500
Mean	50.13	8.36	11.83	50.60	8.97	10.26
Median	51.84	8.23	11.84	51.84	8.98	10.68
Std	9.96	0.45	2.26	6.01	0.90	2.25

6 Conclusion and future work

This study utilizes the EDMOA within the heuristic algorithm domain to identify the parameters that lead to successful basketball shots, conducting an in-depth analysis of scoring strategies and tactics. EDMOA, an enhancement of DMOA, accelerates convergence and aids in

escaping local optima. This paper leverages EDMOA to investigate comprehensive basketball shooting strategies and tactics, yielding a more extensive set of shooting parameters—such as shooting distance , height, initial velocity, and angle—compared to existing research. It provides scientifically precise shooting recommendations and scrutinizes the interrelationship among shooting parameters influencing shooting effectiveness. Furthermore, this approach identifies feasible parameter combinations for successful three-pointers and free throws, analyzing their impact and offering sensible shooting advice for both. Lastly, it delves into the shooting strategies and tactics for athletes of varying heights, uncovering distinctive shooting parameters for different athlete types and discerning the disparities in shooting strategies. Future research aims to build on this foundation, developing a system to enhance basketball shooting accuracy. This system intends to facilitate the formulation of training programs for basketball coaches and provide visual guidance for basketball players, ultimately enhancing shooting accuracy.

Data availability

All data generated or analysed during this study are included in this published article [and its supplementary information files].

Author contributions

Q.L.: Supervisor, Writing - review & editing. **S.L.:** Methodology, Writing - original draft. **H. H.:** Experimental, Software. **Y. Z.:** Supervisor,Writing - review & editing.

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Competing interests

The authors declare that they have no competing interests.

Additional information Correspondence and requests for materials should be addressed to S.L.

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