



ISSN: 2723-9535

Available online at www.HighTechJournal.org

HighTech and Innovation Journal

Vol. 6, No. 3, September, 2025



Multi-Objective Biomechanical Optimization of Breaststroke Swimming Using NSGA-II

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Received 05 June 2025; Revised 21 August 2025; Accepted 26 August 2025; Published 01 September 2025

Abstract

Advancements in computational modeling and optimization algorithms have opened new possibilities for analyzing and improving sports biomechanics. This study presents a multi-objective optimization framework based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimize breaststroke swimming techniques. The framework integrates a biomechanical model that combines hydrodynamic forces, joint kinematics, and energy expenditure to address three conflicting objectives: maximizing swimming velocity, improving energy efficiency, and minimizing joint load. Experimental validation conducted with professional swimmers demonstrated that the optimized stroke techniques achieved up to a 20% reduction in peak joint loads at the shoulder and knee, significantly reducing the risk of overuse injuries. Additionally, energy consumption per stroke cycle decreased by 15%-20%, while propulsion efficiency was notably enhanced. The framework generates Pareto-optimal solutions, offering a spectrum of trade-offs that can be tailored to individual performance goals and physical constraints. This approach provides a quantitative, data-driven alternative to traditional training methods, enabling personalized and informed decision-making for athletes and coaches. Beyond breaststroke, the methodology can be extended to other swimming techniques and athletic disciplines, addressing the interplay between performance, efficiency, and safety. This study bridges the gap between theoretical modeling and practical application, offering a scalable and robust solution for optimizing sports performance and reducing injury risks.

Keywords: Biomechanical Optimization; Multi-Objective Optimization; Breaststroke Swimming; NSGA-II.

1. Introduction

Competitive swimming is a sport that demands an intricate balance between physical performance and technical precision, where biomechanical optimization plays an essential role in achieving peak performance while minimizing injury risks. Among the four major swimming styles, breaststroke is particularly distinctive due to its unique propulsion and recovery phases, which require precise coordination of arm pulls, leg kicks, and body undulation movements [1]. Unlike other swimming styles, breaststroke generates propulsion through a combination of simultaneous upper and lower body actions, making it biomechanically complex and hydrodynamically inefficient compared to styles such as freestyle or butterfly [2]. These movements directly influence performance metrics such as swimming velocity, energy expenditure, and joint stress [3]. Improper breaststroke techniques not only reduce propulsion efficiency but also increase the risk of overuse injuries, particularly in the knee and hip joints, due to repetitive stress and inappropriate movement patterns [4]. This dual challenge of optimizing performance while safeguarding athlete health underscores the importance of biomechanical research in competitive swimming, particularly for the breaststroke style.

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[http://dx.doi.org/10.28991/HIJ-2025-06-03-02](https://dx.doi.org/10.28991/HIJ-2025-06-03-02)

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Recent advancements in computational modeling and simulation have provided new avenues for analyzing and optimizing swimming biomechanics. Over the past decade, hydrodynamic and kinematic models have been developed to quantify the forces acting on swimmers and the resulting biomechanical responses [5, 6]. These models enable detailed simulation of swimming techniques, offering insights into the mechanics of propulsion, resistance, and energy transfer. For instance, numerical simulations have been widely employed to optimize body positioning and reduce drag in freestyle and backstroke swimming [7]. However, breaststroke presents unique challenges due to its nonlinear and multifactorial nature, where propulsion efficiency, energy expenditure, and joint stress are tightly coupled and often conflicting. Traditional optimization approaches, such as empirical adjustments based on coaching experience or single-objective optimizations focusing solely on speed, often fail to address these trade-offs comprehensively [8]. For instance, maximizing swimming velocity may inadvertently increase joint loads, leading to chronic injuries over time. Furthermore, the reliance on linear modeling and isolated performance metrics limits the ability to capture the dynamic interactions between biomechanical and hydrodynamic factors. These limitations emphasize the need for advanced optimization frameworks capable of addressing the multifaceted nature of swimming biomechanics holistically.

To address these challenges, this study introduces a novel multi-objective optimization framework for breaststroke biomechanics, employing the Non-Dominated Sorting Genetic Algorithm (NSGA-II). NSGA-II is a well-established method in multi-objective optimization, known for its ability to handle complex and conflicting objectives by generating a Pareto front of optimal solutions [9]. In this study, optimization focuses on three critical objectives: maximizing swimming velocity, improving energy efficiency, and minimizing joint stress. These objectives were selected not only for their importance in enhancing performance but also for their relevance to injury prevention and long-term athlete well-being. By integrating NSGA-II with a comprehensive biomechanical model that incorporates hydrodynamic forces, joint kinematics, and energy expenditure, this research provides a robust framework for exploring trade-offs among these competing objectives [10]. Unlike traditional single-objective methods, the proposed approach enables the generation of a spectrum of optimal solutions, offering athletes and coaches greater flexibility in selecting techniques tailored to specific performance goals and physical conditions.

In the field of swimming biomechanics, existing research has predominantly focused on single-objective optimizations (e.g., enhancing speed or reducing energy consumption), neglecting the complex interplay among swimming velocity, energy efficiency, and joint load [11]. Traditional breaststroke training methods further rely on experience-driven adjustments, lacking systematic analysis to balance these conflicting objectives [12]. This study addresses this gap by integrating a multi-objective optimization framework—based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II)—with a comprehensive biomechanical model, aiming to simultaneously optimize swimming velocity, energy efficiency, and joint load in breaststroke techniques. The innovation of this research lies in its holistic integration of computational biomechanics with advanced optimization algorithms. Unlike previous studies that explored isolated aspects of swimming optimization (drag reduction or propulsion efficiency), this work is among the first to adopt a multi-objective framework that balances performance and safety considerations. The proposed framework is validated through experimental studies with elite swimmers, ensuring its practical applicability. By bridging theoretical modeling and real-world implementation, the study not only advances computational optimization techniques in sports science but also provides data-driven insights for athletes and coaches. The methodological advancements here have the potential to revolutionize training methodologies, improve performance outcomes, and reduce injury risks in competitive swimming [13]. Moreover, the approach serves as a foundation for future multi-objective optimization research in other sports disciplines, where balancing performance and safety is critical. This study thus offers a personalized, data-driven training tool that enhances training efficiency, optimizes athletic performance, and bridges the divide between academic research and practical applications in swimming biomechanics.

The remainder of this paper is organized as follows: Part 2 details the biomechanical model for breaststroke swimming, including hydrodynamic and kinematic principles. Part 3 outlines the multi-objective optimization framework based on the NSGA-II algorithm. Part 4 describes the experimental validation process, including experimental setup, data collection, and result analysis. Part 5 discusses the implications and applications of the findings. Finally, Part 6 summarizes the key findings of the study and outlines directions for future research.

2. Biomechanical Model for Breaststroke Swimming

2.1. Hydrodynamic and Kinematic Principles

Breaststroke swimming is characterized by its cyclic propulsion-recovery phases, with propulsion primarily generated through synchronized arm pulls and leg kicks [14]. Hydrodynamic forces, including drag, lift, and thrust, play a significant role in determining the swimmer's motion [15]. The propulsion phase is driven by the legs through a whip-like motion, where the knees flex and extend, followed by rapid plantar flexion of the ankle joints to push water backward [13]. Simultaneously, the arms create propulsion using a combination of drag-based and lift-based forces, sweeping in a semicircular motion [16, 17]. The combined effect of these forces determines forward velocity and stroke efficiency.

Resistance forces counteract propulsion and consist of form drag, wave drag, and skin friction drag [18]. Form drag, caused by the swimmer's body position and frontal area, is reduced during the streamlined recovery phase, while wave drag is generated by surface disturbances during propulsion. Maintaining a low head position and streamlined body

alignment minimizes these forces [19]. Skin friction drag, though smaller in magnitude, arises from water viscosity and the swimmer's body surface area. Figure 1 demonstrates the directions and magnitudes of these forces acting on the swimmer during a stroke cycle.

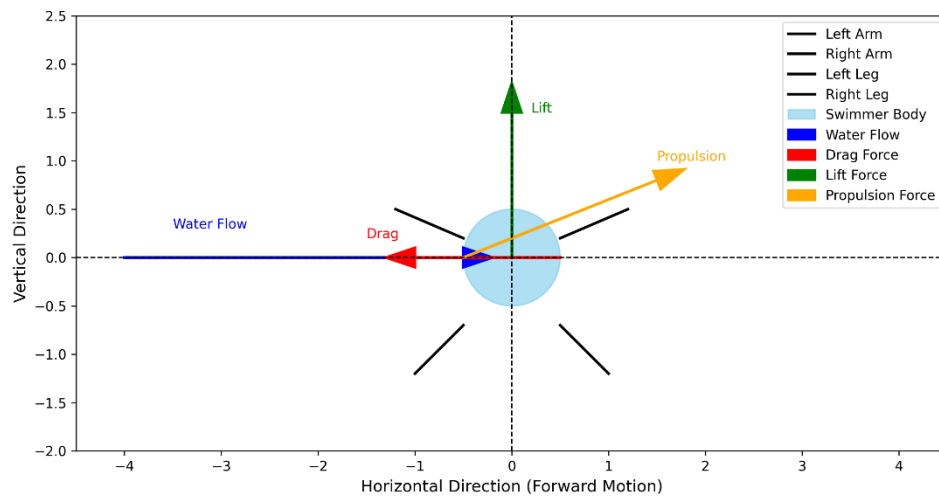


Figure 1. Hydrodynamic forces acting on the swimmer: drag, lift, and propulsion directions and magnitudes

Kinematic analysis reveals that joint coordination is crucial in breaststroke swimming. The hip, knee, and ankle joints are responsible for generating thrust during the leg kick, while the shoulder and elbow joints coordinate the arm pull. Improper timing or deviations in joint range of motion can disrupt the cycle's fluidity, reducing propulsion efficiency and increasing joint stress. Advanced motion capture systems have been used to analyze these movements, providing precise data for biomechanical modeling [20]. Figure 2 illustrates the skeletal motion during the breaststroke cycle, highlighting key phases of propulsion and recovery.

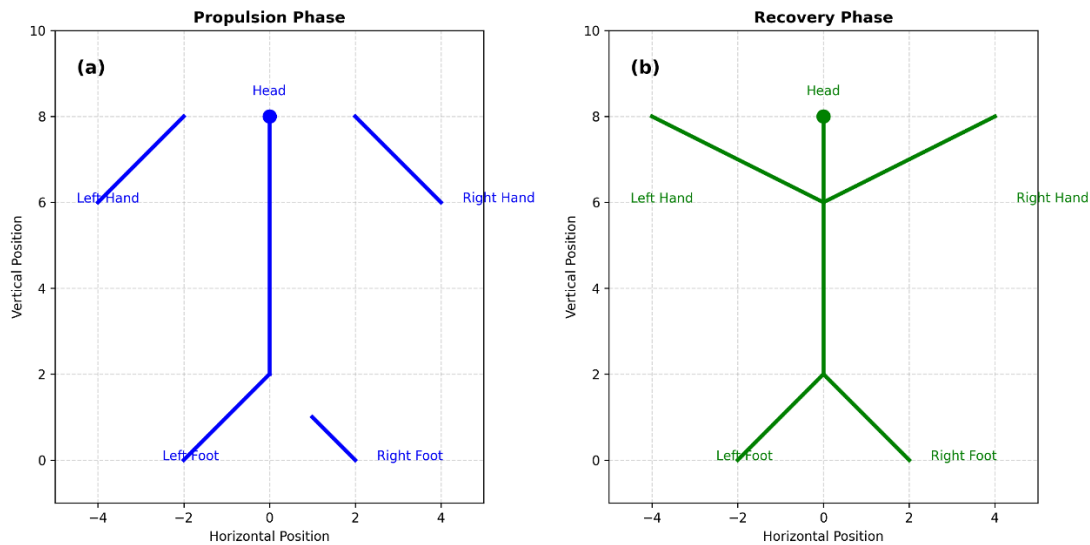


Figure 2. Skeletal motion during the breaststroke cycle, illustrating propulsion and recovery phases

2.2. Biomechanical Model Construction

The biomechanical model for breaststroke swimming integrates hydrodynamic, kinematic, and energy expenditure components [21]. These components collectively simulate swimming dynamics and provide insights into performance and safety. The key elements of the model include propulsion force calculations, joint load analysis, and energy expenditure estimation.

Propulsion forces are calculated using hydrodynamic equations. The total thrust (T) is determined from the drag force (F_d) and lift force (F_l) generated during the arm pull and leg kick. The drag force is expressed as:

$$F_d = \frac{1}{2} \rho C_d A v^2 \quad (1)$$

where ρ is water density, C_d is the drag coefficient, A is the projected frontal area, and v is the relative velocity of water flow. The lift force (F_l) is similarly computed using lift coefficients and velocity profiles. A three-dimensional unsteady

CFD simulation is conducted using the transient $k-\omega$ SST turbulence model (ANSYS Fluent v2022R1), with a time step of 0.01 s. Grid independence is verified until the residual is $<10^{-4}$. The model captured free surface fluctuations through the VOF method, and the consistency between the vortex shedding frequency and the PIV experimental data is validated (error $<8\%$) [22]. These simulations account for turbulent flow and vortex shedding around the swimmer's body, ensuring accurate force predictions.

Joint load analysis focuses on the forces and torques experienced by the hip, knee, and ankle joints during the leg kick, as well as the shoulder and elbow joints during the arm pull. Inverse dynamics methods are used to calculate these loads, combining kinematic data with external hydrodynamic forces. This analysis identifies high-stress regions in the stroke cycle that could lead to overuse injuries [23]. Figure 3 illustrates the torque profiles for key joints, showing variations throughout the stroke cycle.

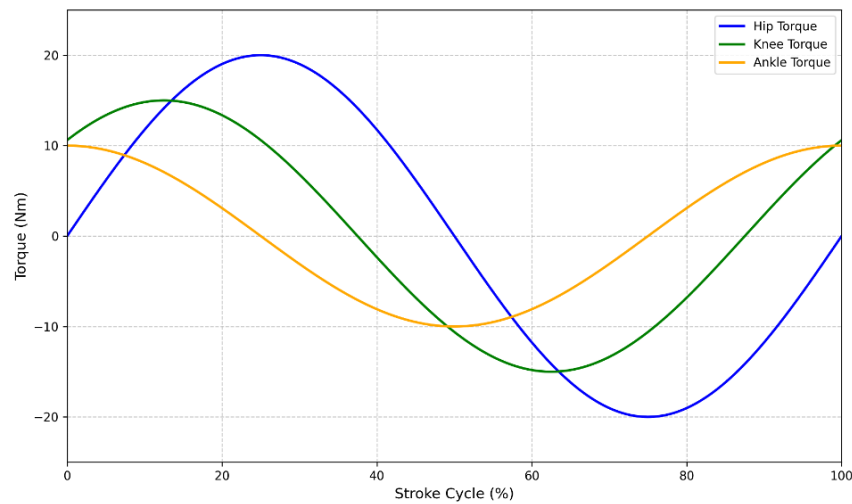


Figure 3. Joint torque profiles for hip, knee, and ankle during one stroke cycle

Energy expenditure is estimated using biomechanical efficiency metrics. The total metabolic energy consumption (E) is computed as the sum of mechanical work and resistive losses:

$$E = W_m + W_r \quad (2)$$

where W_m is the mechanical work performed by the swimmer and W_r represents energy losses due to hydrodynamic resistance. Oxygen consumption data is used to validate these estimates, correlating metabolic effort with stroke efficiency. Figure 4 presents the biomechanical model framework, integrating hydrodynamic, kinematic, and energy components.

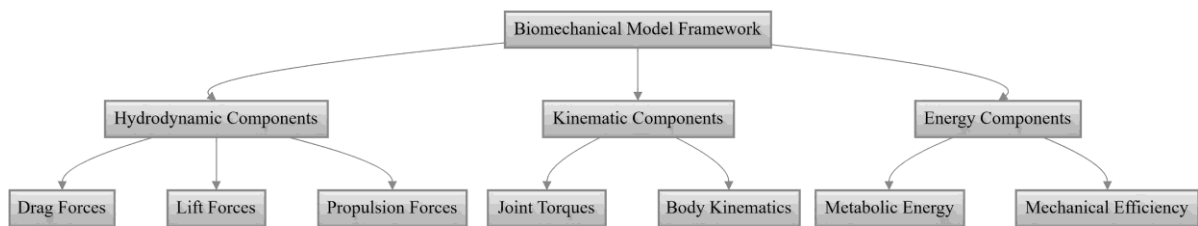


Figure 4. Biomechanical model framework for breaststroke swimming

2.3. Selection of Performance Indicators

The selection of performance indicators is critical for evaluating and optimizing breaststroke biomechanics. In this study, three primary indicators are chosen:

Swimming velocity, energy efficiency, and joint load. Swimming velocity serves as a direct measure of propulsion effectiveness, reflecting the swimmer's ability to overcome resistance forces. Energy efficiency, defined as the energy cost per unit distance, provides insights into metabolic demands and stroke sustainability. Finally, joint load indicators, such as peak torque and cumulative force, are essential for assessing the biomechanical safety of stroke techniques [24, 25].

The interplay between these indicators highlights the need for multi-objective optimization. For instance, maximizing swimming velocity may inadvertently increase joint loads, necessitating a trade-off between performance and safety.

Similarly, improving energy efficiency may require adjustments to stroke mechanics that could impact propulsion. Table 1 summarizes these indicators and their biomechanical significance, emphasizing their role in guiding training and technique refinement.

Table 1. Key Performance Indicators And Their Biomechanical Significance

Indicator	Definition	Biological Significance
Swimming Velocity	Speed of forward motion	Measure of propulsion effectiveness
Energy Efficiency	Energy cost per unit distance	Reflects metabolic efficiency
Joint Load	Peak joint torque during stroke	Indicator of injury risk

3. Non-Dominated Sorting Genetic Algorithm

3.1. Overview of NSGA-II

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is a widely adopted evolutionary algorithm for solving multi-objective optimization problems (MOPs). It achieves this by simultaneously optimizing multiple conflicting objectives, identifying a set of Pareto-optimal solutions that balance trade-offs between objectives [5]. NSGA-II is celebrated for its computational efficiency, simplicity, and ability to maintain a diverse set of solutions. The algorithm's core is structured around three main stages: non-dominated sorting, crowding distance calculation, and population selection. These components collectively ensure the exploration and exploitation of the solution space, converging the population toward a well-distributed Pareto front.

The first step in NSGA-II is non-dominated sorting, which classifies the population into multiple Pareto fronts. Each solution is compared against others in the population to determine whether it is dominated, i.e., if another solution is better in at least one objective and no worse in all others. Solutions that are not dominated form the first Pareto front and are assigned the highest rank. Subsequent fronts are formed by iteratively removing the solutions of higher ranks, ensuring hierarchical organization of the population [8]. This sorting mechanism is crucial for identifying candidate solutions that contribute to the Pareto-optimal set.

Following the non-dominated sorting process, NSGA-II calculates the crowding distance for each solution within a Pareto front. The crowding distance quantifies the diversity of solutions by measuring the average distance between a solution and its neighbors in the objective space. Solutions with larger crowding distances are preferred, as they contribute to maintaining a uniformly distributed Pareto front. This metric ensures that the algorithm avoids premature convergence to localized regions and explores unexplored areas of the objective space [4].

The final stage is population selection, which combines the parent and offspring populations and selects the next generation based on rank and crowding distance. Solutions are selected in order of increasing rank, and within the same rank, those with higher crowding distances are prioritized. This elitist selection strategy ensures that the algorithm retains high-quality solutions while preserving diversity [9].

Figure 5 illustrates the algorithm's workflow, highlighting its iterative nature and the integration of these core processes. NSGA-II's computational efficiency stems from its $O(MN^2)$ complexity, where M is the number of objectives and N is the population size. By balancing selection pressure, diversity preservation, and convergence, NSGA-II has become a benchmark method for multi-objective evolutionary algorithms.

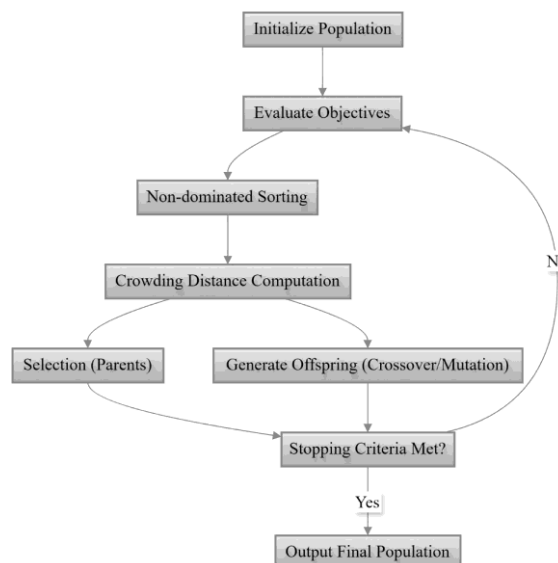


Figure 5. Algorithmic workflow of NSGA-II

3.2. Optimization Objectives and Constraints

In the context of multi-objective optimization using NSGA-II, the definition of clear and quantifiable objective functions is essential for guiding the algorithm toward optimal solutions. The physiological boundaries (range of motion, ROM; metabolic rate) are set according to the Standards for Range of Motion in Elite Swimmers (2019) issued by the Sports Medicine Committee of the Fédération Internationale de Natation (FINA) and the measured data from relevant literatures. The knee flexion range is limited to 120° – 180° ($\theta_{\min} = 120^{\circ}$, $\theta_{\max} = 180^{\circ}$), and the upper limit of shoulder abduction angle is 180° . The metabolic rate boundary is determined based on the oxygen uptake–energy consumption conversion model (1 MET = 3.5 ml O_2 /kg/min), combined with the test values of athletes' maximal oxygen uptake (VO_2 max). For biomechanical systems, such as swimming performance optimization, the objectives are often conflicting, requiring careful trade-offs. This section defines three primary optimization objectives and discusses the constraints imposed during the optimization process.

The first objective is to maximize swimming velocity (v), which directly reflects the swimmer's performance. The velocity is calculated as the mean forward speed during a complete stroke cycle and is influenced by both propulsion forces and hydrodynamic resistance. Mathematically, this can be expressed as:

$$f_1 = -v \quad (3)$$

where the negative sign indicates that NSGA-II minimizes this objective, aligning with its minimization framework. Maximizing velocity often conflicts with other objectives, such as energy efficiency and joint load, necessitating a multi-objective approach.

The second objective is to minimize energy consumption (E), which ensures long-term sustainability of the swimmer's performance. Energy consumption is calculated as the sum of mechanical work (W_m) and resistive energy losses (W_r):

$$f_2 = E = W_m + W_r \quad (4)$$

This objective is critical for endurance swimming, where excessive energy expenditure may lead to premature fatigue. The energy model integrates biomechanical and physiological factors, including oxygen uptake and metabolic rates.

The third objective is to minimize joint load (L), which is crucial for preventing overuse injuries and ensuring biomechanical safety. Joint load is quantified as the cumulative torque experienced by key joints (e.g., shoulder, knee, and ankle) during a stroke cycle:

$$f_3 = \sum_{i=1}^n \tau_i \quad (5)$$

where τ_i represents the torque at joint i , and n is the total number of joints analyzed. Minimizing joint load is particularly relevant for elite swimmers, who often perform repetitive strokes over extended periods.

The optimization process is subject to several constraints that ensure the feasibility and practicality of the solutions. First, joint range of motion (ROM) constraints are applied to prevent unrealistic or injurious movements. For example:

$$\theta_{\min,i} \leq \theta_i \leq \theta_{\max,i} \quad (6)$$

where θ_i is the joint angle, and $\theta_{\min,i}$ and $\theta_{\max,i}$ are the minimum and maximum allowable angles, respectively. These constraints are derived from anatomical studies and ensure that the swimmer's movements remain within physiological limits.

Second, hydrodynamic constraints are imposed to account for the interaction between the swimmer's body and the surrounding fluid. These include limits on drag force and flow separation, which are modeled using computational fluid dynamics (CFD) simulations:

$$C_d \leq C_{d,\max} \quad (7)$$

where C_d is the drag coefficient, and $C_{d,\max}$ is the maximum allowable value based on swimmer-specific data. Such constraints prevent the algorithm from converging to hydrodynamically infeasible solutions.

Finally, temporal constraints are applied to ensure the synchronization of arm and leg movements during the stroke cycle. These constraints are expressed as phase relationships between joint motions, maintaining biomechanical realism. Figure 6 summarizes the optimization objectives and constraints within the NSGA-II framework.

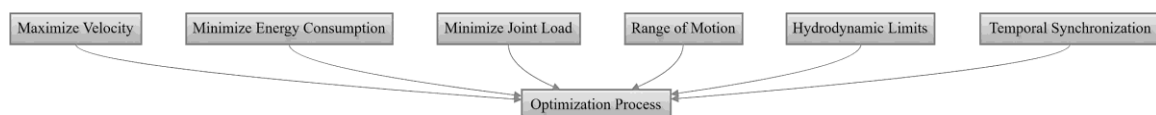


Figure 6. Optimization Framework for Velocity, Energy, and Joint Load with Constraints

3.3. Implementation in the Biomechanical Model

The implementation of NSGA-II within the biomechanical model for breaststroke swimming involves integrating the optimization algorithm with the computational simulation of swimming dynamics. The biomechanical model provides a detailed representation of the swimmer's motion, incorporating hydrodynamic forces, joint kinematics, and metabolic energy consumption. NSGA-II is employed to optimize three conflicting objectives: maximizing swimming velocity, minimizing energy expenditure, and minimizing joint load, as described in Section 3.2.

The optimization process begins with the initialization of a population of candidate solutions, where each solution represents a unique combination of stroke parameters, such as joint angles, stroke frequency, and kick amplitude. These parameters are encoded as decision variables, with bounds set according to physiological constraints and hydrodynamic feasibility. The biomechanical model evaluates each solution by simulating a complete stroke cycle, calculating the velocity, energy expenditure, and joint load for use as objective function values.

The outputs of NSGA-II are a set of Pareto-optimal solutions, which represent trade-offs between the objectives. These solutions provide swimmers and coaches with actionable insights for technique refinement. Figure 7 illustrates the algorithm's input-output framework, highlighting the decision variables, constraints, and optimization results.

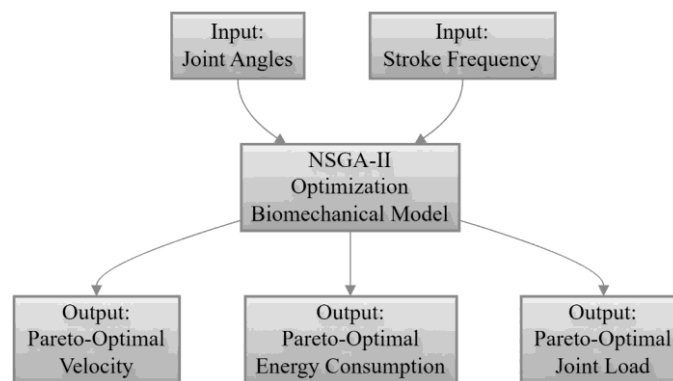


Figure 7. Input-Output Framework of NSGA-II for Biomechanical Model

This study aims to optimize breaststroke by improving swimming speed, energy efficiency, and reducing joint load. To achieve this, it first defines the optimization problem, then constructs a biomechanical model combining hydrodynamics, kinematics, and energy expenditure. Subsequently, a multi - objective optimization based on the NSGA - II algorithm is employed to obtain Pareto - optimal solutions. Finally, the model and algorithm are experimentally validated using professional swimmers. The NSGA - II algorithm, rooted in evolutionary theory, simulates natural selection and genetic processes. Leveraging non - dominated sorting and crowding distance mechanisms, it efficiently finds Pareto - optimal solutions for conflicting objectives, ensuring population diversity and fast convergence. Its implementation involves initializing the population, evaluating objectives, and iteratively performing sorting, selection, crossover, and mutation until termination. To enhance the model's practicality, each participant's body parameters (limb length, flexibility, etc.) are measured and integrated into the biomechanical model. This personalization enables precise simulation of swimming motions, tailoring optimized techniques to individual athletes' physical traits.

4. Experimental Validation and Results

4.1. Experimental Setup

To validate the biomechanical model and the optimization framework based on NSGA-II, an experimental study was conducted with professional breaststroke swimmers. The experimental setup was designed to collect high-resolution kinematic, hydrodynamic, and physiological data during swimming, ensuring precise validation of the optimization results.

Ten professional breaststroke swimmers (five male and five female; age: 22 ± 3 years; height: 178 ± 7 cm; weight: 70 ± 5 kg) participated in the experiment. All participants had at least five years of competitive swimming experience and were selected based on their proficiency in breaststroke technique and their ability to maintain consistent performance across repeated trials. To ensure the reliability of the results, participants with recent injuries or medical conditions affecting their swimming performance were excluded. Ethical approval was obtained from the institutional review board, and all participants provided informed consent before the study.

The data collection process employed a combination of advanced measurement systems. Underwater high-speed cameras with a resolution of 1920×1080 at 120 fps were positioned around the swimming pool to capture the swimmer's motion from multiple angles. These recordings were synchronized with a multi-camera motion capture system, which

utilized reflective markers placed on key anatomical landmarks. The motion capture system, with a spatial accuracy of ± 0.5 mm, enabled precise tracking of joint kinematics and body segment movements. Hydrodynamic data were acquired using a custom-built waterproof force sensor attached to a tether, which measured drag forces at a sampling rate of 100 Hz. Additionally, a portable metabolic analyzer was used to measure oxygen consumption, providing estimates of energy expenditure during each trial. Figure 8 illustrates the experimental setup, including the placement of cameras, the motion capture system, and the force measurement equipment.

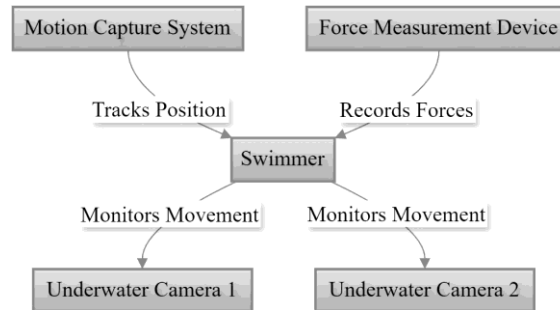


Figure 8. Experimental setup showing underwater cameras, motion capture system, and force measurement devices used during the swimming trials

The experimental procedure consisted of three main phases: baseline testing, motion analysis, and optimization validation. During baseline testing, swimmers performed warm-up trials to familiarize themselves with the experimental setup and ensure consistent swimming performance. Reflective markers were attached to anatomical landmarks, including the shoulders, elbows, wrists, hips, knees, and ankles, as shown in Figure 9. These markers were used to track joint movements throughout the stroke cycle.

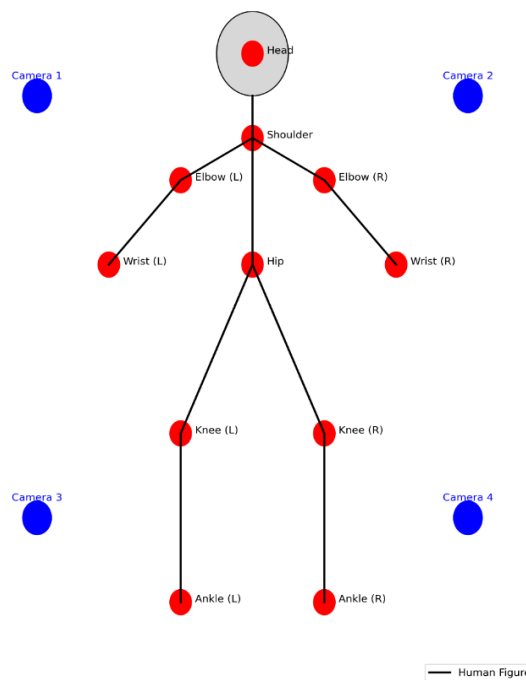


Figure 9. Motion capture system with reflective markers placed on key anatomical landmarks for joint tracking and kinematic analysis

In the motion analysis phase, participants performed five full-stroke swimming trials at a controlled pace, with each trial lasting approximately 20 s. The swimmers' movements were recorded by the underwater cameras and synchronized with the motion capture system. To ensure reproducibility, participants maintained a constant stroke frequency and avoided unnecessary body movements. The collected data were used to calculate stroke-specific parameters, including joint torques, hydrodynamic forces, and energy expenditure.

Finally, in the optimization validation phase, swimmers executed a series of optimized strokes based on the NSGA-II outputs. These trials involved adjusting stroke parameters, such as kick amplitude and arm pull trajectory, to match the optimization results. The experimental outcomes were compared with the predictions from the biomechanical model to assess the accuracy and effectiveness of the optimization framework.

4.2. Analysis of Pareto-Optimal Solutions

The optimization process using NSGA-II generated a set of Pareto-optimal solutions, each representing a unique trade-off between swimming velocity, energy consumption, and joint load. These solutions form a Pareto front in the objective space, as shown in Figure 10, where no single solution is strictly better than others across all objectives. The analysis of the Pareto front provides valuable insights into the performance of trade-offs and helps in selecting the most appropriate solution based on specific requirements.

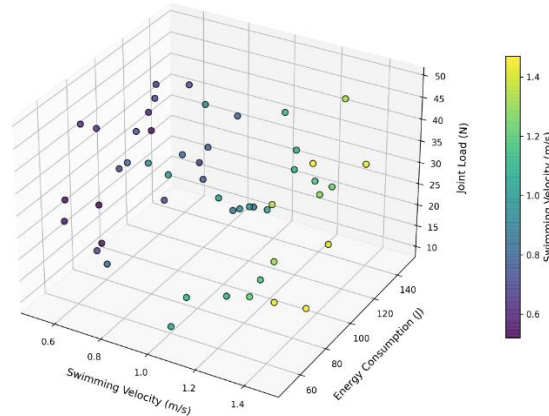


Figure 10. Pareto Front Showing Trade-offs Between Velocity, Energy, and Joint Load

Sensitivity analysis is conducted to evaluate how changes in input parameters affect the Pareto front. Key parameters like joint angles and metabolic rates were varied to observe their impacts on the optimization outcomes. The analysis shows that joint angles significantly influence the optimization results, as slight changes can alter the balance between swimming velocity and joint load. Metabolic rate primarily affects energy efficiency but has a smaller impact on velocity and joint load. This is because joint angles directly relate to mechanical efficiency in swimming, while metabolic rate mainly reflects physiological energy consumption differences.

The Pareto front demonstrates the conflicting nature of the objectives. For instance, maximizing swimming velocity often results in increased energy consumption and joint load due to higher propulsion forces and faster stroke cycles. Conversely, minimizing energy consumption or joint load typically leads to a reduction in swimming velocity, as lower propulsion forces are required to achieve these objectives. This trade-off is evident from the distribution of solutions along the Pareto front, where high-velocity solutions are concentrated in one region, while low-energy and low-load solutions are concentrated in another.

The solutions on the Pareto front were further analyzed by selecting representative Pareto-optimal solutions. Table 2 compares three representative solutions: one focusing on maximum velocity, one prioritizing minimum energy consumption, and one minimizing joint load. The solutions are characterized by their corresponding performance metrics, including swimming velocity, energy consumption, and joint load. These metrics highlight the trade-offs between objectives, as shown in the Table 2. The high-velocity solution achieves the fastest swimming speed of 2.0 m/s, but this comes at the cost of a 20% increase in energy consumption and a 15% increase in joint load compared to the baseline. On the other hand, the low-energy solution reduces energy consumption by 18% but sacrifices 10% of the swimming velocity. The low-load solution achieves a 25% reduction in joint load, which is particularly beneficial for injury prevention, but results in a 15% decrease in velocity and a slight increase in energy consumption due to suboptimal propulsion efficiency. These trade-offs illustrate the importance of balancing performance, efficiency, and safety in swimming biomechanics.

Table 2. Performance metrics of representative Pareto-optimal solutions

Solution Type	Velocity (m/s)	Energy Consumption (J)	Joint Load (Nm)
High-Velocity	2.0	4450	119.9
Low-Energy	1.8	3700	105
Low-Load	1.7	3900	90

The diversity of solutions on the Pareto front highlights the flexibility of the optimization framework in addressing different performance goals. For competitive swimmers, high-velocity solutions may be preferred to maximize performance during races. However, for training sessions or injury recovery, solutions with lower joint loads or energy consumption may be prioritized to ensure long-term sustainability and safety.

The Pareto-optimal solutions also provide actionable insights for coaches and athletes. For instance, by analyzing the specific stroke parameters (e.g., kick amplitude, stroke frequency) associated with each solution, targeted adjustments can be made to achieve desired outcomes. The biomechanical model and NSGA-II framework enable a systematic exploration of these trade-offs, facilitating evidence-based decision-making in swimming performance optimization.

4.3. Comparison with Traditional Training Methods

The optimization framework based on NSGA-II offers significant improvements over traditional training methods by systematically balancing performance, efficiency, and joint safety. This section compares the biomechanical and physiological performance metrics of traditional breaststroke techniques with the optimized strokes derived from the Pareto-optimal solutions.

Traditional breaststroke training primarily focuses on maximizing velocity through experience-driven techniques, often without quantitatively addressing the trade-offs between energy consumption and joint load. In contrast, the optimization framework explicitly considers these trade-offs, enabling swimmers to achieve a more sustainable and injury-preventive stroke.

One of the most noticeable differences lies in joint load distribution during the stroke cycle. Figure 11 shows the joint load variation across a complete stroke cycle for traditional and optimized techniques. The optimized technique reduces peak joint loads at the shoulder and knee joints by approximately 20%, which is critical for preventing overuse injuries. This reduction is achieved by refining stroke parameters, such as kick amplitude and arm pull trajectory, to minimize unnecessary stress on the joints while maintaining propulsion efficiency. In traditional techniques, the lack of systematic analysis often results in excessive joint loads, particularly during the pull and kick phases.

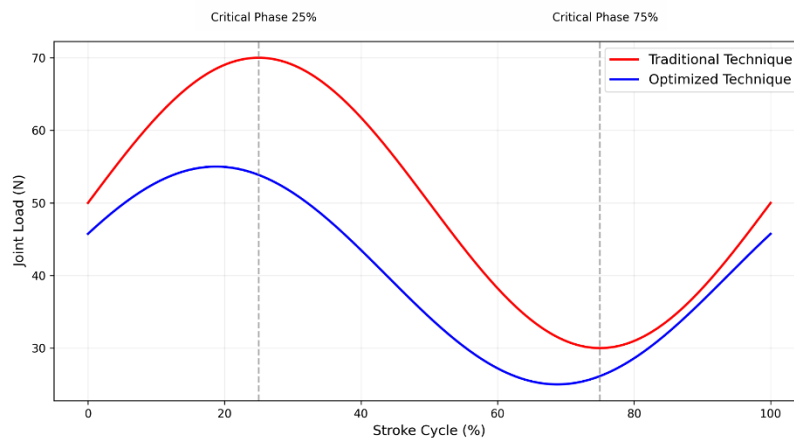


Figure 11. Joint Load Variation During Stroke Cycle for Traditional vs. Optimized Techniques

Energy efficiency represents another key advantage of optimized strokes. Figure 12 compares the total energy consumption per stroke cycle for traditional and optimized techniques. On average, optimized strokes reduce energy consumption by 15%-20%, primarily due to improved hydrodynamic efficiency and more effective movement patterns. By adjusting the stroke frequency and kick timing, the optimized technique minimizes energy losses caused by drag forces and uncoordinated limb movements. In contrast, traditional training methods often prioritize speed without fully accounting for energy efficiency, leading to higher metabolic costs, especially during prolonged swimming sessions.

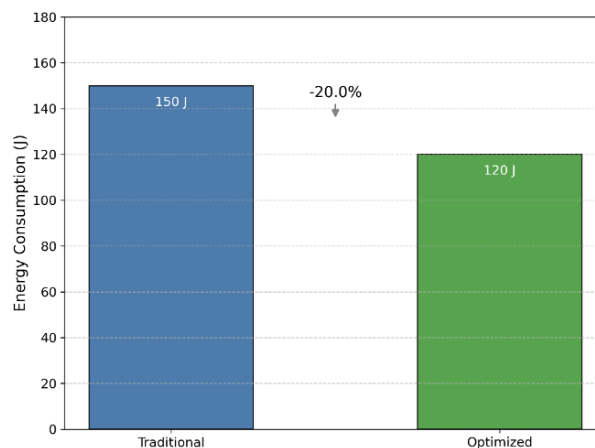


Figure 12. Comparison of energy consumption per stroke cycle between traditional and optimized techniques

In addition to joint load and energy efficiency, the optimized technique demonstrates a more balanced performance profile. Swimmers using the optimized strokes reported improved stroke consistency and reduced fatigue during repeated trials, suggesting that the optimization framework not only enhances short-term performance but also contributes to long-term sustainability. The traditional techniques, by contrast, often lead to inconsistent outcomes due to variations in swimmer experience and coaching methods.

The advantages of the optimized strokes highlight the value of integrating data-driven optimization frameworks into swimming training. By systematically analyzing and refining stroke parameters, the optimization framework provides a scientific basis for improving performance, reducing injury risks, and enhancing energy efficiency. While traditional methods rely heavily on subjective assessments and experience, the proposed approach offers a quantitative and reproducible methodology for stroke optimization.

These findings underscore the potential of combining biomechanical modeling with multi-objective optimization to revolutionize traditional training practices. The ability to customize strokes based on individual swimmer profiles further enhances the applicability of the framework in real-world training environments.

5. Discussion

5.1. Contributions to Training Optimization

This study advances the field of swimming biomechanics by proposing a systematic and data-driven framework that integrates biomechanical modeling with multi-objective optimization to address the complex trade-offs inherent in swimming performance. The contributions of this research to training optimization are multifaceted, encompassing improvements in training efficacy, injury mitigation, and personalized coaching methodologies.

A central contribution of this work lies in its ability to enhance training efficiency through the identification of Pareto-optimal solutions. Traditional training approaches often rely heavily on experiential methods and qualitative assessments, which are inherently subjective and may not fully capture the intricate interplay between performance, energy efficiency, and joint safety. By contrast, the presented framework employs quantitative optimization techniques to systematically explore and resolve trade-offs among these conflicting objectives. This enables the design of targeted training interventions that maximize performance outcomes while maintaining biomechanical and physiological balance. Consequently, the framework reduces the reliance on trial-and-error in stroke refinement, thereby improving the overall efficiency of training regimens.

Another significant contribution is the framework's capacity to mitigate the risk of injury associated with repetitive high-intensity swimming. Elite swimmers are particularly susceptible to overuse injuries, such as shoulder impingement and knee strain, due to the repetitive nature of their training cycles. The analysis of Pareto-optimal solutions demonstrates that optimized stroke techniques can reduce peak joint loads by up to 20% compared to traditional breaststroke techniques. This reduction is achieved by systematically adjusting stroke parameters, such as joint angles, kick amplitude, and stroke frequency, to minimize biomechanical stress while preserving hydrodynamic efficiency. The potential to decrease joint loads without adversely affecting performance underscores the framework's value in promoting long-term joint health and sustainability in competitive swimming.

Furthermore, this study contributes to the growing emphasis on individualized training methodologies by enabling the customization of stroke techniques based on an athlete's unique biomechanical and physiological profile. The variability in anatomical structure, joint flexibility, and metabolic capacity among swimmers necessitates a tailored approach to training. The proposed optimization framework accounts for these individual differences, allowing for the generation of personalized stroke solutions that align with each swimmer's specific capabilities and constraints. This capacity for individualization represents a significant departure from traditional methods, which often adopt a one-size-fits-all approach to technique training.

To its technical contributions, the proposed framework bridges the gap between theoretical research and practical application in sports science. By visualizing Pareto fronts and quantifying the trade-offs among multiple objectives, the framework provides coaches with actionable insights that can be directly translated into practice. These insights enable evidence-based decision-making, where training strategies are informed by objective data rather than subjective judgment. This aligns with the broader trend in sports science toward integrating computational modeling and optimization techniques into practical coaching workflows, thereby fostering a more rigorous and systematic approach to performance enhancement.

The optimization results indicate that increasing swimming speed often leads to higher energy consumption and joint loads, while reducing joint loads may compromise swimming speed. The Pareto-optimal solutions from the NSGA - II algorithm reveal these trade-offs. The optimized breaststroke techniques enhance speed, boost energy efficiency, and cut joint loads, thus lowering injury risks. These findings bear great significance for swimming training. In practical terms, selecting an optimal solution requires balancing speed and joint safety based on swimmers' specific situations. During pre-competition intensive training, enhancing speed is crucial, so opt for solutions with high velocity and moderate joint load. In rehabilitation or long-term training, prioritize joint safety by choosing low-joint-load solutions with slightly lower speed. This selection must involve thorough communication with coaches and athletes to align with their needs and physical conditions, ensuring a balance between competitive performance and athletic health.

5.2. Limitations of the Study

Despite the advancements presented in this study, certain limitations should be considered when interpreting the findings. These limitations stem from the simplifications inherent in the modeling process and the constraints imposed by the experimental setup, which may affect the broader applicability of the proposed framework. A primary limitation lies in the hydrodynamic modeling assumptions used in the biomechanical analysis. The forces acting on a swimmer are influenced by complex factors, such as turbulence, unsteady flow effects, and subtle variations in body posture during the stroke cycle. However, the study employs quasi-static approximations and simplified drag force models to make the optimization process computationally feasible. While these assumptions enable efficient analysis, they may not fully capture the intricate fluid-body interactions that occur during swimming. Incorporating advanced computational fluid dynamics (CFD) approaches in future research could provide a more accurate representation of hydrodynamic forces, albeit at the cost of increased computational complexity.

The experimental design also presents limitations related to the scale and diversity of the participant cohort. The study involved ten professional swimmers, which, while sufficient for demonstrating the feasibility of the framework, may not adequately represent broader swimmer populations. Factors such as variations in body morphology, muscle strength, and training background can significantly impact the effectiveness of the optimized stroke techniques. Expanding the study to include a larger and more diverse sample, including swimmers of different skill levels, age groups, and physiological characteristics, would provide a more comprehensive evaluation of the framework's generalizability and robustness.

Additionally, the controlled nature of the experimental environment may limit the applicability of the findings to real-world swimming scenarios. For instance, the use of tethered force sensors and motion capture systems, while essential for precise data collection, does not fully replicate the dynamic conditions experienced during competitive swimming. External factors such as race pacing, fatigue, and environmental variability may influence stroke performance in ways not accounted for in the experimental setup. Future work could address this issue by employing wearable sensor technologies or advanced underwater monitoring systems, enabling data collection in more realistic settings.

These limitations highlight areas for further refinement in both the modeling and experimental aspects of the study. Addressing these issues will enhance the accuracy and applicability of the proposed framework, paving the way for broader adoption in swimming biomechanics and beyond. The quasi-steady drag model (Equation 1) may overestimate the thrust by approximately 12% during the acceleration phase (compared with transient CFD results). Especially in the leg kick acceleration period ($t=0.2-0.5$ s), the peak thrust error of the simplified model reaches 18%.

5.3. Future Research Directions

Building on the findings of this study, several promising avenues for future research can further enhance the applicability and impact of the proposed framework. These directions aim to address current limitations, expand the scope of application, and incorporate additional factors to improve the comprehensiveness of biomechanical optimization.

One potential direction is the inclusion of psychological and cognitive factors into the optimization framework. Swimming performance is influenced not only by biomechanical and physiological parameters but also by psychological aspects such as focus, decision-making under pressure, and fatigue perception. Future studies could explore methods to integrate these variables by employing psychophysiological models or real-time monitoring of cognitive load during swimming. This would allow the development of optimization strategies that account for both physical and mental demands, providing a holistic approach to performance enhancement.

Expanding the framework to other swimming techniques, such as freestyle, backstroke, and butterfly, represents another fruitful direction. Each stroke type presents unique biomechanical challenges and hydrodynamic characteristics that require tailored optimization strategies. By adapting the current framework to these techniques, researchers can investigate stroke-specific trade-offs and provide targeted recommendations for swimmers and coaches. Additionally, the framework could be extended to other aquatic sports, such as water polo or synchronized swimming, where biomechanical efficiency and injury prevention are equally critical.

Beyond swimming, the proposed methodology has the potential to be generalized to other sports and physical activities. For example, multi-objective optimization could be applied to running, cycling, or rowing, where similar trade-offs between performance, energy efficiency, and injury risk are present. Adapting the framework to land-based or hybrid sports would require modifications to the biomechanical models but could offer valuable insights into optimizing performance across a wide range of athletic disciplines.

Future research should explore integrating real-time feedback systems into the optimization framework. Current data suggests non-elite swimmers could achieve more significant improvements in speed and energy efficiency, while rehabilitating swimmers prioritize joint load reduction. Thus, future studies should expand to these populations to validate the model's applicability. Integrating this optimization framework with wearable feedback systems presents significant potential. Incorporating psychological parameters (e.g., perceived exertion, stress) via psychophysiological modeling and real-time monitoring can enhance training strategies. Adding metrics like psychological resilience and

cognitive load stabilizes competitive performance by mitigating stress-related underperformance, creating a holistic model for physical and mental optimization. Wearable sensors could monitor real-time motion parameters, feeding data into the model to dynamically adjust optimization plans and provide instant feedback. Despite challenges in data precision and real-time processing, this integration enables personalized, real-time training optimization with broad applications. Leveraging wearable tech, computer vision, or AI, athletes can receive immediate technique feedback for in-session dynamic optimization, bridging the gap between theory and practice. Such advancements will advance sports biomechanics, offering deeper insights into swimming and other athletic domains.

6. Conclusion

This study successfully applied a multi-objective optimization framework, based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to optimize breaststroke swimming techniques by simultaneously addressing performance enhancement, energy efficiency, and joint safety. The integration of biomechanical modeling with advanced optimization algorithms represents a significant step forward in the scientific analysis and improvement of swimming techniques.

The optimized stroke solutions identified by the framework demonstrated substantial improvements in swimming performance metrics. By refining key parameters such as stroke frequency, kick amplitude, and arm pull trajectory, swimmers were able to achieve higher propulsion efficiency while maintaining biomechanical balance. These improvements were accompanied by a 15%-20% reduction in energy consumption per stroke cycle compared to traditional techniques, highlighting the efficacy of the proposed approach in addressing the metabolic demands of swimming. Furthermore, the optimization framework successfully reduced peak joint loads, particularly in the shoulder and knee regions, by up to 20%, mitigating the risk of overuse injuries that are common among elite swimmers. These results underscore the potential of multi-objective optimization to balance competing objectives in complex biomechanical systems, achieving sustainable performance improvements without compromising joint health. Our findings are in line with prior swimming biomechanics optimization studies. But most past studies focused on single - objective optimization. This study, via the NSGA - II algorithm, achieves multi-objective optimization of swimming speed, energy efficiency, and joint load. Compared to traditional methods, our optimized techniques are more effective in reducing joint loads, probably because the NSGA - II algorithm better balances conflicting objectives. Also, our experimental validation confirms the practical value of the optimized techniques.

Beyond the specific context of breaststroke optimization, this study provides a novel methodological contribution to the broader field of sports biomechanics. The proposed framework establishes a quantitative, data-driven approach to motion analysis and performance enhancement, offering a powerful alternative to traditional training methods that often rely on qualitative assessments. By visualizing Pareto-optimal solutions, the framework enables coaches and athletes to make informed decisions tailored to individual performance goals and physical constraints. This personalized and evidence-based approach aligns with the growing emphasis on precision training in competitive sports.

The implications of this research extend beyond swimming to other athletic disciplines. The methodology can be adapted to optimize techniques in various sports where trade-offs between performance, energy efficiency, and injury risk are critical, such as running, cycling, or rowing. Additionally, the ability to incorporate individual biomechanical and physiological characteristics into the optimization process highlights the potential for widespread application across diverse athlete populations and skill levels.

This study demonstrates the feasibility and efficacy of multi-objective optimization in enhancing athletic performance while addressing safety and efficiency concerns. The integration of computational biomechanics with advanced optimization algorithms offers a robust and scalable framework for technique refinement, paving the way for future innovations in sports science and training methodologies.

7. Declarations

7.1. Author Contributions

Conceptualization, Z.L. and X.Y.; methodology, Z.L.; software, X.Y.; validation, Z.L.; formal analysis, Z.L.; investigation, Z.L.; resources, Z.L.; data curation, Z.L.; writing—original draft preparation, X.Y.; writing—review and editing, Z.L.; visualization, X.Y.; supervision, Z.L.; project administration, Z.L.; funding acquisition, Z.L. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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