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A Systemic Review on the Adoption of Particle Swarm Optimization Algorithms in Biomedical Engineering Diagnostics and Simulations

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Abstract

In biomedical engineering, Particle Swarm Optimization (PSO) algorithms have been increasingly adopted for diagnostics and simulations due to their ability to optimize parameters and improve the accuracy of results effectively. Despite the growing interest in the adoption of PSO algorithms in biomedical engineering, there is a lack of comprehensive understanding of their effectiveness and limitations in diagnostics and simulations. Existing studies have focused on specific applications or case studies. Still, there is a need for a systematic review to synthesize the current state of knowledge and provide insights into the potential benefits and challenges of using PSO algorithms in this context. This study adopted a systematic review comprising a rigorous methodology to identify relevant studies on adopting PSO algorithms in biomedical engineering diagnostics and simulations. A comprehensive search strategy was also developed to identify relevant literature from significant databases. The findings revealed that PSO algorithms have been successfully applied in various biomedical applications, including image processing, signal analysis, and medical image reconstruction. This study reported improvements in accuracy, efficiency, and robustness compared to traditional optimization methods, highlighting the potential of PSO algorithms in enhancing the performance of biomedical engineering systems. The findings suggest that PSO algorithms have the potential to significantly improve the accuracy and efficiency of biomedical engineering systems, but further research is needed to address the challenges and limitations associated with their implementation.

Keywords: Particle swarm optimization, Biomedical engineering, Algorithms, Diagnostics, Simulations.

1 | Introduction

Particle Swarm Optimization (PSO) algorithms have gained significant attention in biomedical engineering for their ability to solve complex optimization problems efficiently [1]. These algorithms are inspired by the social behaviour of bird flocking and fish schooling, where individuals work together to find the optimal

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solution to a problem. PSO algorithms are a population-based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling. The algorithm starts with a population of candidate solutions, called particles, which move through the search space to find the optimal solution [2], [3]. Each particle adjusts its position based on its own experience and the experience of its neighbors to converge toward the global optimum. In the context of biomedical engineering, PSO algorithms have been used in diagnostics and simulations to improve the accuracy and efficiency of various processes [4], [5]. From a technical perspective, PSO algorithms are characterized by their simplicity, ease of implementation, and ability to handle high-dimensional search spaces. These algorithms are particularly well-suited for problems with non-linear and non-convex objective functions, which are common in biomedical engineering applications.

Additionally, PSO algorithms are highly parallelizable, making them suitable for implementation on parallel computing platforms to further enhance their efficiency. Regarding technology, PSO algorithms have been integrated into various software tools and platforms used in biomedical engineering research [6], [7]. These tools provide researchers and practitioners with user-friendly interfaces for configuring and running PSO algorithms and for visualizing and analyzing the optimization results. The availability of these tools has facilitated the widespread adoption of PSO algorithms in biomedical engineering applications. The adoption of PSO algorithms in biomedical engineering diagnostics and simulations has been driven by the need for more accurate and reliable methods for analyzing complex biological data. Traditional optimization algorithms often struggle to find the global optimum in high-dimensional spaces, making them less effective for solving complex biomedical problems.

On the other hand, PSO algorithms have been shown to be highly effective in finding the global optimum by iteratively updating the positions of particles in the search space based on their own best position and the best position found by the group [8], [9]. PSO algorithms have been widely used in biomedical engineering for diagnostics and simulations because they efficiently search for optimal solutions in complex and high-dimensional spaces. The historical evolution of PSO algorithms in this field can be traced back to their inception in the early 1990s by Kennedy and Eberhart, who were inspired by the social behavior of birds flocking and fish schooling. Since then, PSO algorithms have undergone significant developments and adaptations to suit the specific needs of biomedical engineering applications [10], [11].

2 | Key Milestones on the Particle Swarm Optimization Algorithms

PSO algorithms have gained significant attention in solving complex optimization problems in biomedical engineering diagnostics and simulations, marking the following key milestones.

I. The development of novel optimization techniques that leverage the unique capabilities of PSO algorithms: Researchers have explored different variations of PSO algorithms, such as hybrid PSO algorithms that combine PSO with other optimization techniques, to enhance their performance in biomedical applications [12], [13]. For example, hybrid PSO algorithms have been used to optimize the parameters of machine-learning models for disease diagnosis, leading to improved accuracy and efficiency in biomedical diagnostics [14].

II. The integration of PSO algorithms with advanced imaging techniques for medical image analysis: PSO algorithms have been successfully applied to optimize the segmentation and classification of medical images, enabling more accurate and reliable diagnosis of various medical conditions. By leveraging the power of PSO algorithms, researchers have developed automated systems for medical image analysis that can assist healthcare professionals in making informed decisions about patient care [15], [16].

III. The adoption of PSO algorithms in biomedical simulations has really improved the modeling of complex biological systems: PSO algorithms have been used to optimize the parameters of computational models in areas such as drug design and personalized medicine, leading to more accurate predictions and insights into the behavior of biological systems [17]. By incorporating PSO algorithms into biomedical simulations, researchers have been able to accelerate the discovery of new treatments and therapies for various diseases, ultimately improving patient outcomes [18].

IV. The incorporation of constraints and multi-objective optimization techniques: By considering constraints related to the physical limitations of biomedical systems or the trade-offs between competing objectives in diagnostic and simulation tasks, researchers could tailor PSO algorithms better to address the specific challenges of biomedical engineering problems [19]. This has led to the development of more robust and versatile PSO algorithms that can handle various complex optimization problems in biomedical applications [20].

V. The introduction of adaptive PSO variants that could dynamically adjust their parameters during the optimization process allowed for better convergence and improved performance in solving complex optimization problems, such as those encountered in medical image processing and signal analysis. Additionally, researchers have explored the use of hybrid PSO algorithms that combine the strengths of PSO with other optimization techniques, such as genetic algorithms or simulated annealing, to further enhance their capabilities in biomedical engineering applications [21], [22].

The adoption of PSO algorithms in biomedical engineering diagnostics and simulations has significantly advanced the field by enabling researchers to tackle complex optimization problems more effectively. Key milestones in this adoption include the development of novel optimization techniques, integrating PSO algorithms with advanced imaging techniques, and using PSO algorithms in biomedical simulations [23]. Moving forward, continued research and innovation in applying PSO algorithms in biomedical engineering will further enhance the capabilities of biomedical systems and improve patient care.

3 | Implementing Particle Swarm Optimization Algorithms in Biomedical Engineering Diagnostics and Simulations

In biomedical engineering, PSO algorithms have been widely used for diagnostics and simulations due to their ability to find optimal solutions promptly. The detailed procedure for implementing PSO algorithms in biomedical engineering diagnostics and simulations is as follows.

I. Problem formulation: The first step in implementing a PSO algorithm in biomedical engineering is clearly defining the optimization problem. This involves identifying the objective function to be optimized and any constraints that need to be considered. For example, in diagnosing a disease using medical imaging data, the objective function may be to minimize the error between the predicted and actual diagnosis [24].

II. Initialization: Once the problem has been formulated, the next step is to initialize the population of particles. This involves randomly generating a set of candidate solutions within the search space. Each particle represents a potential solution to the optimization problem and is characterized by its position and velocity in the search space [25].

III. Fitness evaluation: After initializing the population, the fitness of each particle is evaluated using the objective function. This involves calculating the fitness value of each particle based on how well it satisfies the optimization criteria. In the context of biomedical engineering, this may include evaluating the accuracy of a diagnostic model based on the particle's position in the search space [26].

IV. Update particle velocity and position: Once each particle's fitness has been evaluated, the next step is to update its velocity and position. This is done by applying the PSO algorithm, which involves adjusting the particle's velocity based on its own best position and the best position found by the entire population. This allows the particles to move towards the optimal solution in the search space [27].

V. Termination criteria: The optimization process continues iteratively until a termination criterion is met. This criterion may be a maximum number of iterations, a specific level of convergence, or a predefined threshold for the fitness value. Once the termination criterion is met, the algorithm stops and the best solution found by the PSO algorithm is returned as the final result [28].

Implementing PSO algorithms in biomedical engineering diagnostics and simulations involves a systematic approach that includes problem formulation, initialization, fitness evaluation, updating particle velocity and position, and defining termination criteria. By following this detailed step-by-step procedure, researchers and practitioners can effectively apply PSO algorithms to solve complex optimization problems in biomedical engineering.

4 | Key Features of Particle Swarm Optimization Algorithms for Biomedical Engineering Diagnostics and Simulations

In the context of biomedical engineering diagnostics and simulations, PSO algorithms that have been successfully applied to tasks such as feature selection, parameter optimization, and model fitting comprise the following features.

I. The Swarm consists of a group of particles that move through the search space to find the optimal solution to the optimization problem. Each particle represents a potential solution to the optimization problem and moves toward the best solution found by the swarm [29]. Each particle has a position and a velocity, which are updated in each iteration based on its own best-known position (p-best) and the best-known position of its neighbors (g-best). The swarm collectively searches the solution space by adjusting the positions of the particles toward the optimal solution. The swarm dynamics are governed by a fitness function, which evaluates the quality of each particle's solution [30].

II. Fitness function: In biomedical engineering, the fitness function can be tailored to specific diagnostic or simulation tasks, such as maximizing the accuracy of a diagnostic model or minimizing the error in a simulation [31]. This evaluates the quality of a solution based on a set of objective criteria. The fitness function guides the particles in the swarm toward better solutions by providing feedback on their performance. The goal of the PSO algorithm is to minimize or maximize the fitness function, depending on the nature of the optimization problem [32].

III. Inertia weight and acceleration coefficients: These are crucial parameters in PSO algorithms that control the exploration and exploitation capabilities of the swarm. The inertia weight determines the balance between exploration (Searching the solution space) and exploitation (Exploiting the current best solution) [33]. In other words, it controls the balance between exploration and exploitation in the search space. A high inertia weight allows particles to explore new regions of the search space, while a low one helps particles exploit promising areas. However, the acceleration coefficients influence the movement of the particles towards the optimal solution. Tuning these parameters is essential for achieving optimal performance of the PSO algorithm [34]. The acceleration coefficients determine how particles are influenced by their own best solution and the best solution found by the swarm.

IV. Swarm topology: This refers to how particles are organized in the swarm and how they interact. Common swarm topologies include fully connected, ring, and star topologies, each with advantages and disadvantages [35]. The choice of swarm topology can impact the convergence speed and exploration capabilities of the PSO algorithm. In biomedical engineering applications, researchers may experiment with different swarm topologies to find the most effective configuration for their specific optimization problem [36].

In PSO algorithms, particles update their positions and velocities based on several parameters, including the inertia weight, acceleration coefficients, and swarm topology. By adjusting these parameters, users can fine-tune the performance of the PSO algorithm for specific biomedical engineering tasks. POS algorithms offer a powerful tool for solving complex optimization problems in biomedical engineering diagnostics and simulations.

5 | Variants of Particle Swarm Optimization Algorithm for Optimization Problems

Apart from the traditional PSO algorithm, several variants have been proposed in the literature to improve its performance and address specific optimization problems. These variants differ in how they update the particle positions and velocities and in the strategies they use to balance exploration and exploitation. Some of the most commonly used order PSO algorithms include:

I. Constriction Coefficient Particle Swarm Optimization (CCPSO): CCPSO introduces a constriction factor that limits the maximum velocity of particles, preventing them from moving too far away from the best solution found so far (See *Fig. 1*). This helps to maintain a balance between exploration and exploitation and improves convergence speed [37].

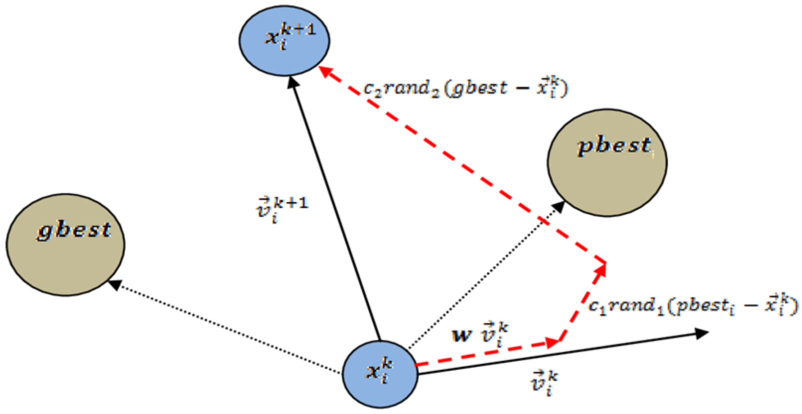

Fig. 1. Constriction coefficient for particle swarm optimization [38].

II. Adaptive Particle Swarm Optimization (APSO): APSO dynamically adjusts the inertia weight and acceleration coefficients during the optimization process based on the particles' performance (See *Fig. 2*). This allows the algorithm to adapt to the problem's characteristics and improve its convergence speed [39].

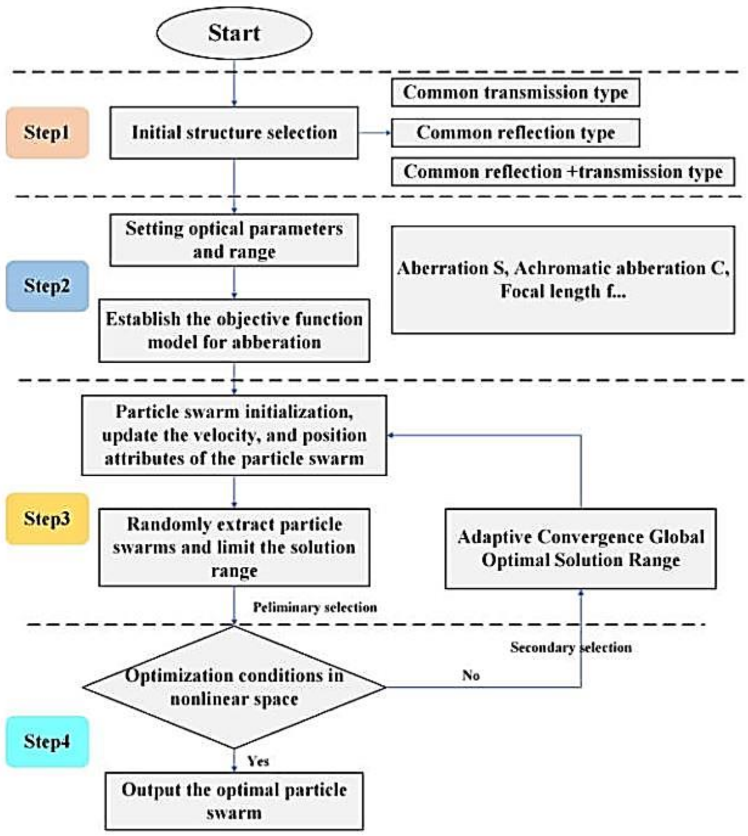

Fig. 2. Adaptive particle swarm optimization [40].

III. Quantum-behaved Particle Swarm Optimization (QPSO): QPSO models particles' behaviour using quantum mechanics principles, such as wave-particle duality and uncertainty, as shown in *Fig. 3*.

This allows particles to explore the search space more efficiently and find better solutions in high-dimensional and multimodal optimization problems [41].

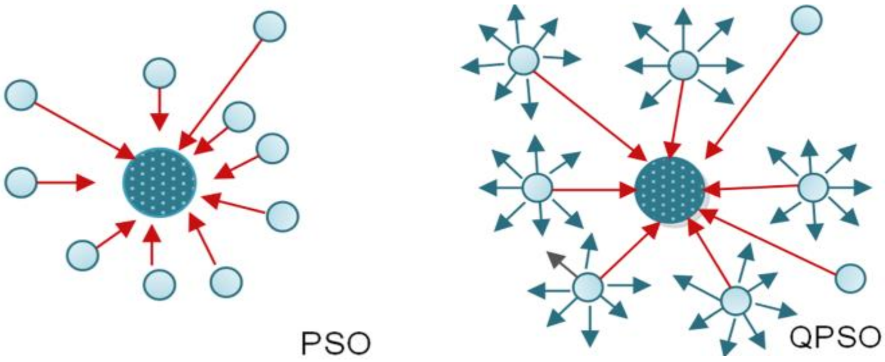

Fig. 3. Quantum-behaved particle swarm optimization [42].

IV. Multi-Objective Particle Swarm Optimization (MOPSO): MOPSO extends the traditional PSO algorithm to handle multiple conflicting objectives simultaneously (See *Fig. 4*). It uses a Pareto-based approach to maintain a set of non-dominated solutions, known as the Pareto front, representing the trade-offs between the objectives [43].

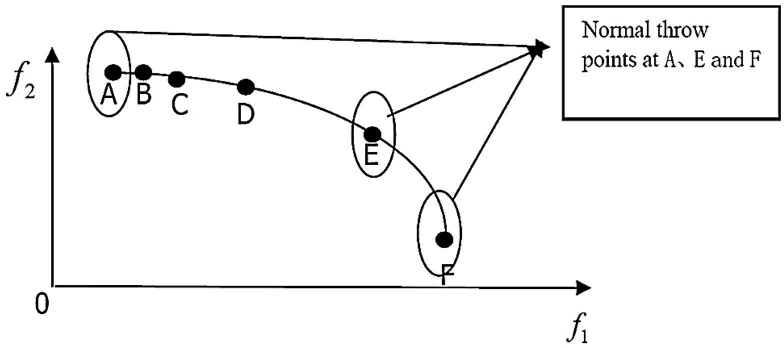

Fig. 4. Multi-objective particle swarm optimization [44].

V. Hybrid PSO: Hybrid PSO algorithms combine PSO with other optimization techniques, such as genetic algorithms, simulated annealing, or local search methods, as shown in *Fig. 5*. This allows the algorithm to benefit from the strengths of different optimization approaches and improve its performance on complex optimization problems [45].

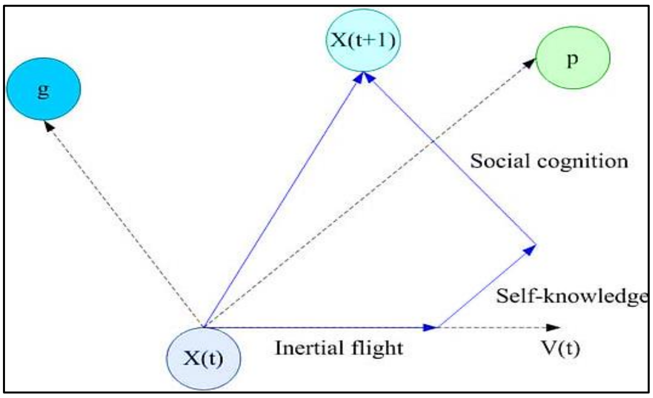

Fig. 5. Hybrid particle swarm optimization [46].

Order PSO algorithms offer various strategies to enhance the performance of the traditional PSO algorithm and address specific optimization challenges. Researchers and practitioners can choose the most suitable variant based on the characteristics of the optimization problem and the desired trade-offs between exploration and exploitation.

6 | Feature Selection in Particle Swarm Optimization Algorithms for Biomedical Engineering Diagnostics

Feature selection is crucial in optimizing particle swarm algorithms for biomedical engineering diagnostics and simulations. It involves identifying the most relevant features from a dataset that will contribute to the accuracy and efficiency of the algorithm. The procedure for feature selection in PSO algorithms for biomedical engineering applications is as follows.

I. Define the objective function of the optimization algorithm: This function should be designed to maximize the algorithm's performance by selecting the most informative features from the dataset. The objective function should take into account the specific requirements of the biomedical engineering application, such as the desired level of accuracy and the computational resources available [47].

II. Initialize the population of particles in the optimization algorithm: Each particle represents a potential solution to the feature selection problem, and the population as a whole explores the search space for the optimal set of features. The particles are initialized with random values for the features, and their positions are updated iteratively based on their performance in the objective function [48].

III. During each iteration of the optimization algorithm, the particles are evaluated based on their fitness in the objective function. The fitness of a particle is determined by its ability to select the most relevant features from the dataset. Particles that perform well in the objective function are more likely to be chosen for further exploration, while particles that perform poorly are discarded [49].

IV. As the optimization algorithm progresses, the particles move through the search space for the optimal set of features. This movement is guided by the principles of swarm intelligence, allowing particles to communicate and share information about the best solutions found so far [50]. This collaboration helps the particles converge on a solution that maximizes the algorithm's performance.

V. Once the optimization algorithm has converged on a solution, the selected features are used to train a machine-learning model for biomedical engineering diagnostics and simulations. This model can then be used to make predictions or analyze data in the biomedical field with the confidence that the selected features are the most relevant for the task at hand [51].

Feature selection is a critical component of PSO algorithms for biomedical engineering applications. By following the procedure outlined in this study, users can effectively identify the most informative features from a dataset and optimize the performance of their algorithms. This approach can lead to more accurate and efficient diagnostics and simulations in biomedical engineering.

7 | Parametric Optimization in Particle Swarm Optimization Algorithms for Biomedical Engineering Diagnostics

The success of PSO algorithms in biomedical engineering for parameter optimization for diagnostics and simulations relies heavily on carefully selecting and tuning its parameters. The procedures are as follows.

I. The first step in parameter optimization for PSO algorithms is selecting appropriate parameters to optimize. These parameters typically include the inertia weight, cognitive, and social parameters. The inertia weight controls the trade-off between exploration and exploitation in the search space. At the same time, the cognitive and social parameters determine the influence of personal and social information on particle movement [52].

II. Once the parameters to be optimized are identified, the next step is to define the search space for each parameter. This involves setting upper and lower bounds for each parameter to ensure the optimization process remains within feasible limits. It is important to carefully consider each parameter's range of values to avoid premature convergence or poor exploration of the search space [53].

III. After defining the search space, the next step is to choose an appropriate fitness function to evaluate the performance of the PSO algorithm. The fitness function should be tailored to the specific biomedical engineering application being studied, considering the problem's objectives and constraints [54]. Common fitness functions in biomedical engineering include classification accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve.

IV. With the parameters, search space, and fitness function defined, the next step is implementing the PSO algorithm and conducting a series of experiments to evaluate its performance. This involves running the algorithm multiple times with different parameter settings and recording the results for each run [55]. It is important to use statistical measures such as mean and standard deviation to analyze the algorithm's performance and compare different parameter settings.

V. Based on the results of the experiments, the final step is to fine-tune the parameters of the PSO algorithm to achieve optimal performance. This can be done by manually adjusting the parameters based on the insights gained from the experimental results or using metaheuristic optimization techniques such as genetic algorithms or simulated annealing [56].

8 | Model Fitting in Particle Swarm Optimization Algorithms during Biomedical Engineering Diagnostics

Model fitting is crucial in utilizing PSO algorithms for diagnostics and simulations in biomedical engineering. To achieve this, the following steps must be carefully adopted:

I. Define the objective function: The objective function represents the model's fitness and evaluates the algorithm's performance. In biomedical engineering, the objective function may be based on experimental data, simulation results, or a combination of both [57].

II. Initialize the population: The population represents a set of potential solutions to the optimization problem. Each particle in the population is assigned a position and velocity, which are updated iteratively during optimization [58].

III. Evaluate the fitness of each particle: The fitness of each particle is evaluated using the objective function. The fitness value represents how well the particle's position fits the model to the experimental data or simulation results [59]. The fitness value determines the particle's contribution to the optimization process.

IV. Update the particle's position and velocity: The position and velocity of each particle are updated using the PSO algorithm. The new position and velocity are calculated based on the particle's previous position and velocity and the best position found by the particle or its neighbors [60].

V. Check for convergence: During the optimization process, monitoring the algorithm's convergence is important. Convergence occurs when the algorithm reaches a stable solution that satisfies the optimization criteria. Convergence can be checked by monitoring the particles' fitness values and the optimization process's overall progress [13].

VI. Terminate the optimization process: The optimization process is terminated when the algorithm converges to a stable solution or reaches a predefined number of iterations. The final solution represents the optimized model that best fits the experimental data or simulation results. The optimized model can be used for diagnostics, simulations, or further analysis in biomedical engineering [61].

Model fitting in PSO algorithms for biomedical engineering diagnostics and simulations involves the aforementioned steps, which include defining the objective function, initializing the population, evaluating the fitness of each particle, updating the particle's position and velocity, checking for convergence, and terminating the optimization process, as shown in the flowchart in *Fig. 6*. By adopting these steps, users can effectively utilize PSO algorithms for optimizing complex models and simulations in biomedical engineering.

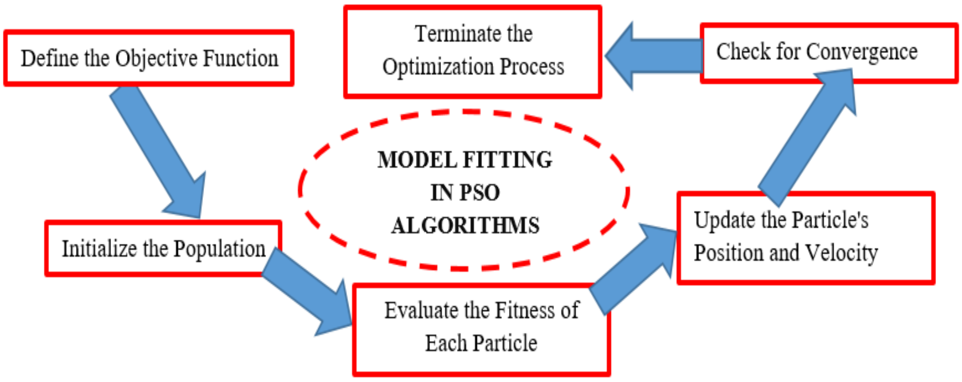

Fig. 6. Flowchart of model fitting in particle swarm optimization algorithms.

9 | Factors Affecting the Implementation Process of Particle Swarm Optimization

In the context of diagnostics and simulations in biomedical engineering, the implementation process of PSO can be influenced by several factors that include the following:

I. Choice of objective function: The objective function is crucial in guiding the optimization process towards finding the optimal solution. In the context of diagnostics and simulations in biomedical engineering, the objective function may be complex and multi-dimensional, making it challenging to define and optimize [62]. The choice of an appropriate objective function is essential for the success of the PSO algorithm in biomedical engineering applications.

II. Selection of parameters: The performance of the PSO algorithm is highly dependent on the values of its parameters, such as the inertia weight, acceleration coefficients, and swarm size. The selection of appropriate parameter values is crucial for achieving good convergence and exploration capabilities of the PSO algorithm [63]. In the context of diagnostics and simulations in biomedical engineering, the selection of parameters may require careful tuning and optimization to ensure the effectiveness of the PSO algorithm.

III. The computational complexity of the optimization problem can also impact the implementation process of PSO in biomedical engineering. Diagnostics and simulations in biomedical engineering often involve large-scale and computationally intensive problems that require efficient optimization algorithms [64]. The computational complexity of the optimization problem can affect the convergence speed and accuracy of the PSO algorithm. In such cases, advanced techniques, such as parallelization and hybridization, may be required to enhance the performance of the PSO algorithm in biomedical engineering applications [65].

IV. The presence of noise and uncertainties in biomedical engineering data can also affect the implementation process of PSO. Noise and uncertainties in data can lead to suboptimal solutions and hinder the convergence of the PSO algorithm [66]. Robust optimization techniques, such as adaptive PSO and dynamic parameter adjustment, may be necessary to effectively handle noise and uncertainties in biomedical engineering data.

V. Various factors can influence t.

he implementation process of PSO in diagnostics and simulations in biomedical engineering, including the choice of the objective function, the selection of parameters, the computational complexity of the optimization problem, and the presence of noise and uncertainties in data. Addressing these factors effectively is essential for the successful application of PSO in biomedical engineering.

10 | Key Areas of Particle Swarm Optimization Application in Biomedical Engineering

The key areas of PSO application in different aspects of biomedical engineering are highlighted as follows:

I. Optimization of diagnostic processes: Diagnostic imaging techniques such as MRI, CT scans, and ultrasound play a crucial role in the early detection and diagnosis of various medical conditions. However, these imaging techniques often involve complex algorithms and parameters that must be optimized for accurate and efficient diagnosis [67]. PSO can be used to optimize these parameters by iteratively adjusting them to maximize the accuracy of the diagnostic process. By fine-tuning the parameters using PSO, researchers can improve the sensitivity and specificity of diagnostic imaging techniques, leading to more accurate and reliable diagnoses [68].

II. Simulation of biological systems: Computational models are often used to simulate the behavior of biological systems, such as the cardiovascular or nervous systems, better to understand their function and dynamics [69]. These models typically involve many parameters that must be optimized to represent the biological system accurately. PSO can be used to optimize these parameters by searching for the optimal set of values that minimize the error between the simulated and observed data. By using PSO to optimize the parameters of computational models, researchers can improve the accuracy and predictive power of these models, leading to a better understanding of complex biological systems [70].

III. Optimization of medical devices and treatment plans: For example, PSO can be used to optimize the design of medical implants, such as pacemakers or prosthetic limbs, by finding the optimal configuration of components that maximize their performance and longevity [71]. Similarly, PSO can be used to optimize treatment plans for diseases such as cancer by adjusting the dosage and schedule of treatments to maximize their effectiveness while minimizing side effects. Researchers can improve patient outcomes and quality of life by using PSO to optimize medical devices and treatment plans [72].

PSO is a versatile optimization technique that has been successfully applied in various areas of biomedical engineering diagnostics and simulations. By optimizing parameters in diagnostic processes, computational models, medical devices, and treatment plans, PSO can improve the accuracy, efficiency, and effectiveness of biomedical engineering applications.

11 | Conclusion

The findings from this study on the adoption of PSO algorithms in biomedical engineering diagnostics and simulations have provided valuable insights into the potential benefits and challenges associated with this approach. PSO can efficiently optimize complex and non-linear problems commonly encountered in medical image analysis and signal processing. PSO algorithms can effectively search for optimal solutions in high-dimensional search spaces by iteratively updating particle positions based on their individual and collective knowledge, leading to improved accuracy and efficiency in diagnostic and simulation tasks. However, despite the promising results, some challenges and limitations have been identified in adopting PSO algorithms in biomedical engineering. These include the need for careful parameter tuning, the potential for premature convergence to suboptimal solutions, and the lack of interpretability in the optimization process.

Additionally, the performance of PSO algorithms may be influenced by the choice of fitness function, swarm size, and inertia weight, which can impact their effectiveness in real-world applications. The findings from this study suggest that while PSO algorithms hold great potential for enhancing the capabilities of biomedical engineering diagnostics and simulations, further research is needed to address the existing challenges and limitations. Future studies should focus on developing novel variants of PSO algorithms specifically tailored to the unique requirements of biomedical applications, as well as on conducting rigorous comparative evaluations with other optimization techniques to establish their superiority in performance and robustness

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Data Availability

The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Mohd Yamin, M. N., Ab. Aziz, K., Siang, T. G., & Ab. Aziz, N. A. (2023). Particle swarm optimisation for emotion recognition systems: A decade review of the literature. *Applied sciences*, *13*(12), 7054. https://doi.org/10.3390/app13127054

[2] Gad, A. G. (2022). Particle swarm optimization algorithm and its applications: A systematic review. *Archives of computational methods in engineering*, *29*(5), 2531–2561. https://doi.org/10.1007/s11831-021-09694-4

[3] Wang, D., Tan, D., & Liu, L. (2018). Particle swarm optimization algorithm: An overview. *Soft computing*, *22*(2), 387–408. https://doi.org/10.1007/s00500-016-2474-6

[4] Lameesa, A., Hoque, M., Alam, M. S. B., Ahmed, S. F., & Gandomi, A. H. (2024). Role of metaheuristic algorithms in healthcare: a comprehensive investigation across clinical diagnosis, medical imaging, operations management, and public health. *Journal of computational design and engineering*, *11*(3), 223–247. https://doi.org/10.1093/jcde/qwae046

[5] Ikpe, A. E., Ohwoekevwo, J. U., & Ekanem, I. I. (2024). Overview of the role of medical robotics in day-to-day healthcare services: A paradigm shift in clinical operations. *Ibom medical journal*, *17*(2), 192–203. https://doi.org/10.61386/imj.v7i2.422

[6] de Melo Menezes, B. A., Kuchen, H., & Buarque de Lima Neto, F. (2022). Parallelization of swarm intelligence algorithms: Literature review. *International journal of parallel programming*, *50*(5), 486–514. https://doi.org/10.1007/s10766-022-00736-3

[7] Sun, Y., Chu, S. C., Hu, P., Watada, J., Si, M., & Pan, J. S. (2022). Overview of parallel computing for meta-heuristic algorithms. *Journal of network intelligence*, *7*(3), 656–684. https://bit.kuas.edu.tw/~jni/2022/vol7/s3/08.JNI0353_r2.pdf

[8] Houssein, E. H., Hosney, M. E., Emam, M. M., Younis, E. M. G., Ali, A. A., & Mohamed, W. M. (2023). Soft computing techniques for biomedical data analysis: Open issues and challenges. *Artificial intelligence review*, *56*(2), 2599–2649. https://doi.org/10.1007/s10462-023-10585-2

[9] Rundo, L., Militello, C., Vitabile, S., Russo, G., Sala, E., & Gilardi, M. C. (2019). A survey on nature-inspired medical image analysis: A step further in biomedical data integration. *Fundamenta informaticae*, *171*(1–4), 345–365. https://doi.org/10.3233/FI-2020-1887

[10] Beni, G. (2020). Swarm intelligence. In *complex social and behavioral systems : Game theory and agent-based models* (pp. 791–818). Springer US. https://doi.org/10.1007/978-1-0716-0368-0_530

[11] Shahzad, M. M., Saeed, Z., Akhtar, A., Munawar, H., Yousaf, M. H., Baloach, N. K., & Hussain, F. (2023). A review of swarm robotics in a nutshell. *Drones*, *7*(4), 269. https://doi.org/10.3390/drones7040269

[12] Sengupta, S., Basak, S., & Peters, R. A. (2018). Particle swarm optimization: A survey of historical and recent developments with hybridization perspectives. *Machine learning and knowledge extraction*, *1*(1), 157–191. https://doi.org/10.3390/make1010010

[13] Tian, D., & Shi, Z. (2018). MPSO: Modified particle swarm optimization and its applications. *Swarm and evolutionary computation*, *41*, 49–68. https://doi.org/10.1016/j.swevo.2018.01.011

[14] Yadav, R. K., & Anubhav. (2020). PSO-GA based hybrid with adam optimization for ANN training with application in medical diagnosis. *Cognitive systems research*, *64*, 191–199. https://doi.org/10.1016/j.cogsys.2020.08.011

[15] Zhang, T., Zhou, P., Zhang, S., Cheng, S., Ma, L., Jiang, H., & Yao, Y.-D. (2024). Bio-inspired optimisation algorithms in medical image segmentation: A review. *International journal of bio-inspired computation*, *24*(2), 65–79. https://doi.org/10.1504/IJBIC.2024.141449

[16] Saifullah, S., & Dreżewski, R. (2024). Advanced medical image segmentation enhancement: A particle-swarm-optimization-based histogram equalization approach. *Applied sciences*, *14*(2), 923. https://doi.org/10.3390/app14020923

[17] Khare, A., & Rangnekar, S. (2013). A review of particle swarm optimization and its applications in solar photovoltaic system. *Applied soft computing*, *13*(5), 2997–3006. https://doi.org/10.1016/j.asoc.2012.11.033

[18] Zhang, Y., Wang, S., & Ji, G. (2015). A comprehensive survey on particle swarm optimization algorithm and its applications. *Mathematical problems in engineering*, *2015*(1), 931256. https://doi.org/10.1155/2015/931256

[19] Fei, Z., Li, B., Yang, S., Xing, C., Chen, H., & Hanzo, L. (2017). A survey of multi-objective optimization in wireless sensor networks: Metrics, algorithms, and open problems. *IEEE communications surveys & tutorials*, *19*(1), 550–586. https://doi.org/10.1109/COMST.2016.2610578

[20] Suriyan, K., & Nagarajan, R. (2024). Particle swarm optimization in biomedical technologies: Innovations, challenges, and opportunities. In *emerging technologies for health literacy and medical practice* (pp. 220–238). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-1214-8.ch011

[21] Jain, M., Saihjpal, V., Singh, N., & Singh, S. B. (2022). An overview of variants and advancements of PSO algorithm. *Applied sciences*, *12*(17), 8392. https://doi.org/10.3390/app12178392

[22] Harrison, K. R., Engelbrecht, A. P., & Ombuki-Berman, B. M. (2018). Self-adaptive particle swarm optimization: A review and analysis of convergence. *Swarm intelligence*, *12*(3), 187–226. https://doi.org/10.1007/s11721-017-0150-9

[23] Xu, M., Cao, L., Lu, D., Hu, Z., & Yue, Y. (2023). Application of swarm intelligence optimization algorithms in image processing: A comprehensive review of analysis, synthesis, and optimization. *Biomimetics*, *8*(2), 235. https://doi.org/10.3390/biomimetics8020235

[24] Razzak, M. I., Naz, S., & Zaib, A. (2018). Deep learning for medical image processing: Overview, challenges and the future. In *classification in bioapps: Automation of decision making* (pp. 323–350). Cham: Springer, Cham. https://doi.org/10.1007/978-3-319-65981-7_12

[25] Bangyal, W. H., Nisar, K., Ag. Ibrahim, A. A. B., Haque, M. R., Rodrigues, J. J. P. C., & Rawat, D. B. (2021). Comparative analysis of low discrepancy sequence-based initialization approaches using population-based algorithms for solving the global optimization problems. *Applied sciences*, *11*(16), 7591. https://doi.org/10.3390/app11167591

[26] Ibrahim, F., Thio, T. H. G., Faisal, T., & Neuman, M. (2015). The application of biomedical engineering techniques to the diagnosis and management of tropical diseases: A review. *Sensors*, *15*(3), 6947–6995. https://doi.org/10.3390/s150306947

[27] Garcia-Gonzalo, E., & Fernandez-Martinez, J. L. (2012). A brief historical review of particle swarm optimization (PSO). *Journal of bioinformatics and intelligent control*, *1*(1), 3–16. http://dx.doi.org/10.1166/jbic.2012.1002

[28] Martí, L., García, J., Berlanga, A., & Molina, J. M. (2016). A stopping criterion for multi-objective optimization evolutionary algorithms. *Information sciences*, *367–368*, 700–718. https://doi.org/10.1016/j.ins.2016.07.025

[29] Juneja, M., & Nagar, S. K. (2016). Particle swarm optimization algorithm and its parameters: A review. *2016 international conference on control, computing, communication and materials (ICCCCM)* (pp. 1–5). IEEE. https://doi.org/10.1109/ICCCCM.2016.7918233

[30] Rini, D. P., Shamsuddin, S. M., & Yuhaniz, S. S. (2011). Particle swarm optimization: Technique, system and challenges. *International journal of computer applications*, *14*(1), 19–26. http://dx.doi.org/10.5120/ijais-3651

[31] Kainz, W., Neufeld, E., Bolch, W. E., Graff, C. G., Kim, C. H., Kuster, N., … ., & Tsui, B. M. W. (2019). Advances in computational human phantoms and their applications in biomedical engineering—a topical review. *IEEE transactions on radiation and plasma medical sciences*, *3*(1), 1–23. https://doi.org/10.1109/TRPMS.2018.2883437

[32] Parsopoulos, K. E., & Vrahatis, M. N. (2002). Recent approaches to global optimization problems through particle swarm optimization. *Natural computing*, *1*(2), 235–306. https://doi.org/10.1023/A:1016568309421

[33] Rezaei, F., & Safavi, H. R. (2020). GuASPSO: A new approach to hold a better exploration–exploitation balance in PSO algorithm. *Soft computing*, *24*(7), 4855–4875. https://doi.org/10.1007/s00500-019-04240-8

[34] Marini, F., & Walczak, B. (2015). Particle swarm optimization (PSO). A tutorial. *Chemometrics and intelligent laboratory systems*, *149*, 153–165. https://doi.org/10.1016/j.chemolab.2015.08.020

[35] Alswaitti, M., Albughdadi, M., & Isa, N. A. M. (2018). Density-based particle swarm optimization algorithm for data clustering. *Expert systems with applications*, *91*, 170–186. https://doi.org/10.1016/j.eswa.2017.08.050

[36] Benuwa, B. B., Ghansah, B., Wornyo, D. K., & Adabunu, S. A. (2016). A comprehensive review of particle swarm optimization. *International journal of engineering research in Africa*, *23*, 141–161. https://doi.org/10.4028/www.scientific.net/JERA.23.141

[37] Mavrovouniotis, M., Li, C., & Yang, S. (2017). A survey of swarm intelligence for dynamic optimization: Algorithms and applications. *Swarm and evolutionary computation*, *33*, 1–17. https://doi.org/10.1016/j.swevo.2016.12.005

[38] Sharma, A., Sharma, A., Jately, V., Averbukh, M., Rajput, S., & Azzopardi, B. (2022). A novel TSA-PSO based hybrid algorithm for GMPP tracking under partial shading conditions. *Energies*, *15*(9), 3164. https://doi.org/10.3390/en15093164

[39] Kessentini, S., & Barchiesi, D. (2015). Particle swarm optimization with adaptive inertia weight. *International journal of machine learning and computing*, *5*(5), 368-373. https://doi.org/10.7763/IJMLC.2015.V5.535

[40] Yue, W., Jin, G., & Yang, X. (2022). Adaptive particle swarm optimization for automatic design of common aperture optical system. *Photonics,* 9(11), 807. https://doi.org/10.3390/photonics9110807

[41] Fallahi, S., & Taghadosi, M. (2022). Quantum-behaved particle swarm optimization based on solitons. *Scientific reports*, *12*(1), 13977. https://doi.org/10.1038/s41598-022-18351-0

[42] Bhatia, A. S., Saggi, M. K., & Zheng, S. (2020). QPSO-CD: Quantum-behaved particle swarm optimization algorithm with cauchy distribution. *Quantum information processing*, *19*(10), 345. https://doi.org/10.1007/s11128-020-02842-y

[43] Patil, D. D., & Dangewar, B. D. (2014). Multi-objective particle swarm optimization (MOPSO) based on pareto dominance approach. *International journal of computer applications*, *107*(4). http://dx.doi.org/10.5120/18738-9983

[44] Sun, Y., & Gao, Y. (2019). A multi-objective particle swarm optimization algorithm based on gaussian mutation and an improved learning strategy. *Mathematics*, *7*(2), 148. https://doi.org/10.3390/math7020148

[45] Mirsadeghi, E., & Khodayifar, S. (2021). Hybridizing particle swarm optimization with simulated annealing and differential evolution. *Cluster computing*, *24*(2), 1135–1163. https://doi.org/10.1007/s10586-020-03179-y

[46] Guo, E., Gao, Y., Hu, C., & Zhang, J. (2023). A hybrid PSO-DE intelligent algorithm for solving constrained optimization problems based on feasibility rules. *Mathematics*, *11*(3), 522. https://doi.org/10.3390/math11030522

[47] Brezočnik, L., Fister, I., & Podgorelec, V. (2018). Swarm intelligence algorithms for feature selection: A review. *Applied sciences*, *8*(9), 1521. https://doi.org/10.3390/app8091521

[48] Ahmad, I. (2015). Feature selection using particle swarm optimization in intrusion detection. *International journal of distributed sensor networks*, *11*(10), 806954. http://dx.doi.org/10.1155/2015/806954

[49] Xue, B., Zhang, M., & Browne, W. N. (2012). New fitness functions in binary particle swarm optimisation for feature selection. *2012 IEEE congress on evolutionary computation* (pp. 1–8). IEEE. https://doi.org/10.1109/CEC.2012.6256617

[50] Tang, J., Liu, G., & Pan, Q. (2021). A review on representative swarm intelligence algorithms for solving optimization problems: Applications and trends. *IEEE/CAA journal of automatica Sinica*, *8*(10), 1627–1643. https://doi.org/10.1109/JAS.2021.1004129

[51] Esmin, A. A., Coelho, R. A., & Matwin, S. (2015). A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data. *Artificial intelligence review*, *44*(1), 23–45. https://doi.org/10.1007/s10462-013-9400-4

[52] Rezaee Jordehi, A., & Jasni, J. (2013). Parameter selection in particle swarm optimisation: A survey. *Journal of experimental & theoretical artificial intelligence*, *25*(4), 527–542. https://doi.org/10.1080/0952813X.2013.782348

[53] Nickabadi, A., Ebadzadeh, M. M., & Safabakhsh, R. (2011). A novel particle swarm optimization algorithm with adaptive inertia weight. *Applied soft computing*, *11*(4), 3658–3670. https://doi.org/10.1016/j.asoc.2011.01.037

[54] Sankaran, K. S., & Kim, J. (2022). Efficient and optimized communication in biomedical sensor networks based on bioinspired particle swarm optimization for medical applications. *Medical engineering & physics*, *110*, 103922. https://doi.org/10.1016/j.medengphy.2022.103922

[55] Fan, H. (2002). A modification to particle swarm optimization algorithm. *Engineering computations*, *19*(8), 970–989. https://doi.org/10.1108/02644400210450378

[56] Lessmann, S., Caserta, M., & Arango, I. M. (2011). Tuning metaheuristics: A data mining based approach for particle swarm optimization. *Expert systems with applications*, *38*(10), 12826–12838. https://doi.org/10.1016/j.eswa.2011.04.075

[57] Chawla, M., & Duhan, M. (2014). Applications of recent metaheuristics optimisation algorithms in biomedical engineering: A review. *International journal of biomedical engineering and technology*, *16*(3), 268–278. https://doi.org/10.1504/IJBET.2014.065807

[58] del Valle, Y., Venayagamoorthy, G. K., Mohagheghi, S., Hernandez, J. C., & Harley, R. G. (2008). Particle swarm optimization: Basic concepts, variants and applications in power systems. *IEEE transactions on evolutionary computation*, *12*(2), 171–195. https://doi.org/10.1109/TEVC.2007.896686

[59] Li, X., & Engelbrecht, A. P. (2007). Particle swarm optimization: An introduction and its recent developments. *Proceedings of the 9th annual conference companion on genetic and evolutionary computation* (pp. 3391–3414). Association for Computing Machinery. https://doi.org/10.1145/1274000.1274118

[60] Gang, M., Wei, Z., & Xiaolin, C. (2012). A novel particle swarm optimization algorithm based on particle migration. *Applied mathematics and computation*, *218*(11), 6620–6626. https://doi.org/10.1016/j.amc.2011.12.032

[61] Ab Wahab, M. N., Nefti-Meziani, S., & Atyabi, A. (2015). A comprehensive review of swarm optimization algorithms. *PloS one*, *10*(5), e0122827. https://doi.org/10.1371/journal.pone.0122827

[62] Azadifar, S., & Ahmadi, A. (2021). A graph-based gene selection method for medical diagnosis problems using a many-objective PSO algorithm. *BMC medical informatics and decision making*, *21*(1), 333. https://doi.org/10.1186/s12911-021-01696-3

[63] Thangamani, M., Satheesh, S., Lingisetty, R., Rajendran, S., & Shivahare, B. D. (2025). Mathematical model for swarm optimization in multimodal biomedical images. In *swarm optimization for biomedical applications* (pp. 86–107). CRC Press. https://doi.org/10.1201/9781032713762

[64] Kaur, S., Kumar, Y., Koul, A., & Kumar Kamboj, S. (2023). A systematic review on metaheuristic optimization techniques for feature selections in disease diagnosis: Open issues and challenges. *Archives of computational methods in engineering*, *30*(3), 1863–1895. https://doi.org/10.1007/s11831-022-09853-1

[65] Lalwani, S., Singhal, S., Kumar, R., & Gupta, N. (2013). A comprehensive survey: Applications of multi-objective particle swarm optimization (MOPSO) algorithm. *Transactions on combinatorics*, *2*(1), 39–101. https://doi.org/10.22108/toc.2013.2834

[66] Agarwal, S., Rani, N., & Vajpayee, A. (2024). Bioinspired algorithms: opportunities and challenges. In *bio-inspired optimization for medical data mining* (pp. 1–30). Wiley Online Library. https://doi.org/10.1002/9781394214211.ch1

[67] Kaur, P., & Singh, R. K. (2023). A review on optimization techniques for medical image analysis. *Concurrency and computation: Practice and experience*, *35*(1), e7443. https://doi.org/10.1002/cpe.7443

[68] Kaur, S., & Singh, J. (2023). Enhancing medical image analysis and disease surveillance in healthcare: A study on pso- aco optimization using swarm intelligence. *2023 2nd international conference on computational modelling, simulation and optimization (ICCMSO)* (pp. 269–276). IEEE. https://doi.org/10.1109/ICCMSO59960.2023.00058

[69] Ul Haq, I. (2024). Diagnosis of neurological disease using bioinspired algorithms. In *bio-inspired optimization for medical data mining* (pp. 227–268). Wiley Online Library. https://doi.org/10.1002/9781394214211.ch12

[70] Casson, C. L., John, S. A., & Ferrall-Fairbanks, M. C. (2023). Mathematical modeling of cardio-oncology: Modeling the systemic effects of cancer therapeutics on the cardiovascular system. *Seminars in cancer biology*, *97*, 30–41. https://doi.org/10.1016/j.semcancer.2023.11.004

[71] Peto, M., García-Ávila, J., Rodriguez, C. A., Siller, H. R., da Silva, J. V. L., & Ramírez-Cedillo, E. (2024). Review on structural optimization techniques for additively manufactured implantable medical devices. *Frontiers in mechanical engineering*, *10*, 1353108. https://doi.org/10.3389/fmech.2024.1353108

[72] Candia, D. A., Játiva, P. P., Azurdia Meza, C., Sánchez, I., & Ijaz, M. (2024). Performance analysis of the particle swarm optimization algorithm in a VLC system for localization in hospital environments. *Applied sciences*, *14*(6), 2514. https://doi.org/10.3390/app14062514