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Impact of Evolutionary Algorithm on Optimization of Nonconventional Machining Process Parameters

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ABSTRACT

This paper presents the optimization of laser beam machining in additive manufacturing of polymer-based material parameters, specifically focusing on cutting speed, gas pressure of nitrogen, and focal point locations, to achieve optimal mean surface roughness. Using a Python environment, three evolutionary algorithms such as, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Firefly Algorithm (FA), were simulated to evaluate their effectiveness in minimizing surface roughness (*Ra*). The results of the three algorithms were validated through a benchmark study employing the Genetic Algorithm. The outcomes indicate that the PSO algorithm outperformed the other methods, demonstrating a superior performance in terms of better mean surface roughness. Specifically, the PSO algorithm achieved a mean surface roughness improvement of 0.44% over GA, and 1.1% and 1.23% over ACO and FA, respectively. Notably, the PSO algorithm demonstrated swift convergence, achieving optimal results as early as the second iteration. The PSO algorithm achieved two optimal mean surface roughness values of 0.9333 µm and 0.9838 µm, with an overall average of 0.9399 µm and a standard deviation of 0.0171 µm across 250 runs. These findings indicate that the PSO algorithm excels in delivering superior results while showcasing rapid convergence, robustness, and consistent repeatability in optimizing laser beam machining parameters.

INTRODUCTION

Nonconventional machining techniques are employed to process hard and brittle materials, including carbides, stainless steel, Hastelloy, nitralloy, waspaloy, and other materials that are unsuitable for conventional machining methods. Non-conventional machining processes utilize alternative energy forms, such as thermal, electrical, and chemical energy, to shape material, distinguishing them from conventional machining methods (Deja & Markopoulos, 2024). Laser Beam Machining (LBM) falls under thermal based nonconventional machining. LBM utilizes a high energy laser beam to generate intense localized heat, which melts and vaporizes the material, enabling precise material removal. Unlike electrical or chemical processes, which rely on electrochemical reactions or material dissolution, LBM is purely a thermal energy

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driven technique. This distinction has been emphasized in the introduction to enhance clarity and ensure a more precise classification within nonconventional machining processes. Nonconventional machining processes such as electrical discharge machining, electrochemical machining, and laser beam machining revolutionize manufacturing precision and capabilities globally (Deja & Markopoulos, 2024). Optimizing machinability measurements and selecting the best cutting conditions are inherently nonlinear challenges. In machining, choosing the optimal cutting conditions enhances productivity, ensures high quality, and minimizes costs (El Hossainy et al., 2023).

Eaysin et al. (2025) optimize laser beam machining parameters for AISI-P20 mold steel using the adaptive network-based fuzzy inference system method, enhancing precision and surface quality in machining processes. Metaheuristic algorithms are advanced optimization techniques designed to solve complex problems where traditional methods fall short. Inspired by natural processes like evolution and swarm intelligence, they efficiently explore large search spaces to find near optimal solutions. These algorithms reduce the risk of early stagnation in suboptimal solutions. Widely used in engineering applications and they enhance problem solving across diverse domains (Radhika & Chaparala, 2018). Metaheuristic algorithms are optimization approaches inspired by different natural events, animal behaviors, biological concepts, physical sciences, human activities, and evolutionary processes. These algorithms can be divided into five categories based on their primary sources of inspiration: evolutionary, swarm, physics, human, and game based. A wide range of optimization problems in science, engineering, technology, and industry can be addressed using these techniques. Successful optimization relies on defining decision variables, constraints, and objective functions, which are the three basic components of mathematical modeling for optimization problems (Dehghani & Trojovský, 2023). Metaheuristic algorithms are designed to provide effective solutions for diverse optimization challenges, differing from traditional optimization techniques in several important ways, including being derivative free, meaning they do not require derivative calculations in the search space, making them simpler and more flexible while enabling them to navigate complex landscapes without the risk of becoming trapped in local optima (Tomar et al., 2024). Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Firefly Algorithms (FA) are powerful tools for optimizing machining parameters, excelling at exploring intricate, multiobjective solution spaces, and helping to identify optimal combinations of cutting speed, feed rate, and depth of cut, ultimately leading to improvements in outcomes such as surface quality, tool life, and productivity (Rana et al., 2018; You et al., 2025). The research outcome of Shrivastava & Pandey (2018) demonstrates that the PSO method, combined with regression analysis, effectively optimizes laser cutting parameters (such as cutting speed, gas pressure, and power) for Inconel 718 sheets, resulting in improved cut quality and reduced kerf width. The study by Kalita et al. (2017) highlights that PSO and GA are effective in optimizing laser beam micro marking process parameters, with PSO outperforming GA in achieving higher marking quality and precision.

PSO, inspired by the collective behavior of bird flocks or fish schools, involves particles representing potential solutions. These particles navigate the search space, adjusting positions based on their own experiences (personal best) and the swarm's overall best (global best). The algorithm iteratively adjusts particle movements using three components: inertia (keeps the particle's direction), cognitive (guides it toward its best-known position), and social (directs it toward the swarm's best position) (Trojovsky & Dehghani, 2023). In machining parameter optimization, PSO models the behavior of particles exploring the solution space for optimal parameters such as cutting speed and feed rate, allowing for efficient convergence on solutions that enhance machining performance, resulting in improved surface quality and higher efficiency. ACO mimics the behavior of ants as they search for the shortest paths to food, simulating how ants deposit pheromones on paths, with stronger pheromone trails indicating more desirable routes, and ants probabilistically choose paths based on pheromone levels, reinforcing better paths over time. In machining parameter optimization, ACO simulates the pheromone-guided search behavior of ants to determine optimal settings for speed, feed rate, and depth of cut, allowing the algorithm to converge toward solutions that enhance machining efficiency and quality while being particularly effective for complex

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problems such as routing and scheduling (Tomar et al., 2024). Firefly optimization mimics the attraction behavior of fireflies, where brighter fireflies attract others, with each firefly representing a potential solution for laser beam machining parameters such as cutting speed, feed rate, and depth of cut, and it helps identify optimal settings by balancing exploration and exploitation to improve machining performance.

A comprehensive review of metaheuristic algorithms is available in the literature (Sharma & Raju, 2024; Tomar et al., 2024; Abdel Basset et al., 2018; Kiani Moghaddam et al., 2019). Rajwar et al. (2023) conducted an exhaustive review of metaheuristic methods, highlighting various challenges associated with their application. Salgotra et al. (2024) provided a tabulated overview of metaheuristic optimization methods, including MATLAB and Python codes for practical implementation. Mitra & Hlavacek (2019) explored biological models in the context of metaheuristic algorithms. In recent studies, Duan et al. (2024) applied the Fire Hawk optimizer algorithm to enhance the efficiency of intelligent electric parking lots, aiming to minimize losses and power consumption. Noel et al. (2023) utilized a metaheuristic algorithm to optimize the performance of lithium-ion cells. Furthermore, Chang et al. (2024) investigated nature inspired metaheuristic methods for various engineering applications.

Within the mechanical engineering domain, Madic et al. (2013) employed different algorithms to optimize machining parameters, enhancing manufacturing efficiency and economic viability. Yildiz et al. (2020) compared the performance of ten metaheuristic algorithms in solving six mechanical engineering problems, while Kumar et al. (2022) provided a comprehensive list of engineering applications of metaheuristic algorithms. Pereira et al. (2022) reviewed algorithms for mechanical engineering problems in areas such as machining, molding, and structural health monitoring. The research by El Hossainy et al. (2023) optimized the machining parameters, enhancing precision and efficiency in manufacturing processes through advanced computational methods namely, genetic algorithm and artificial neural network . The review by Alsaadawy et al. (2024) analyzes how laser cutting parameters affect surface and kerf quality in metals, offering insights for optimizing precision and efficiency in manufacturing.

The literature review underscores the promising potential of employing PSO, ACO, and FA algorithms to systematically compare and evaluate their efficacy in optimizing machining parameters for laser beam machining in additive manufacturing. Such an endeavor is anticipated to offer profound insights into the performance and real-world applicability of these advanced metaheuristic algorithms in practical machining scenarios.

METHODOLOGY

This section is organized into three stages, as detailed below:

Stage 1: Identification of process parameters to develop regression equations.
Stage 2: Development of PSO, ACO, and FA in optimizing process parameters.
Stage 3: Comparison of process parameter optimization by PSO, ACO, and FA with GA .

Stage 1: Identification of Process Parameters

The study by Tura et al. (2021) presents a hybrid approach combining GA and Response Surface Methodology (RSM) to optimize laser beam cutting parameters for stainless steel (SS304), achieving improved cut quality and efficiency. The integration of GA and RSM effectively balances multiple objectives, such as minimizing kerf width and surface roughness, while maximizing material removal rate, demonstrating its potential for precision laser machining applications. Tura et al. (2021) conducted a study on laser beam cutting using the constant parameters such as thickness of the work piece (5 mm), wave length (10.6 µm) and wave mode (continues), focal length (127 mm), assist gas (nitrogen), nozzle shape (conical) and nozzle radius (4 mm), standoff distance (1 mm), laser power (2.2 kW) and AISI 304 stainless

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steel is work piece material. The three input process parameters, such as cutting speed, nitrogen gas pressure, and focal point location, were tested at three different levels, as detailed in Table 1.

Table 1. Process parameters

Process parameter	Levels		
	1	2	3
Cutting speed (X1) in mm/min	2000	2500	3000
Nitrogen pressure (X2) in Bar	9	10.5	12
Focal point position (X3) in mm	-2.5	-1.5	-0.5

The regression model outcome of the experimental studies of Tura et al. (2021) is:

$$Ra = 18.69 - 0.002591\,X1 - 2.394\,X2 + 0.5263\,X3 + 0.09030\,(X2)2 - 0.1812\,(X3)2 + 0.000166\,X1 * X2 - 0.000329\,X1 * X3 \quad (1)$$

Tura et al. (2021) also used a genetic algorithm for optimal process parameters as *X1* = 2028.712, *X2* = 11.389, and *X3* = -2.499, with a predicted mean surface roughness of 0.9374 µm.

Stage 2: Development of Optimization Algorithms PSO, ACO, and FA

PSO, ACO, and FA were selected based on their well-documented effectiveness in solving a wide range of optimization problems, particularly in engineering and computational domains. These algorithms have been extensively studied and benchmarked for computational efficiency. PSO is widely recognized for its simplicity and strong convergence properties. ACO excels in combinatorial optimization tasks, and FA effectively handles multimodal problems. Additionally, their selection was based on prior literature, which highlights their robustness and applicability across different optimization scenarios. While other algorithms like Artificial Bee Colony (ABC) and evolutionary strategies are also effective, PSO, ACO, and FA were chosen due to their established performance, ease of implementation, and suitability for the specific problem domain addressed in this study.

Algorithms PSO, ACO, and FA are explored to determine the optimal process parameters for achieving the best mean surface roughness. The results of the mean surface roughness obtained from these algorithms are compared and presented in Table 3. Additionally, each algorithm was executed multiple times (250 runs) to assess its robustness and repeatability.

Controllable parameters are critical to the convergence of algorithms. Based on studies by Dehghani & Trojovsky (2023), Table 2 shows the summary of controllable parameters utilized in the present study.

Table 2. Controllable parameters

PSO	ACO	FA
• Swarm size: 30 particles. • Inertia weight: 0.7 • Cognitive coefficient (c1): 1.5. • Social coefficient (c2): 2.0. • Velocity clamping (*Vmax*): 10% - 20% of the parameter range. • Number of iterations: 250 • Damping factor (wdamp): 0.99	• Number of ants: 30 • Evaporation rate (ρ): 0.5 • Pheromone importance (α): 1 • Heuristic importance (β): 4 • Initial pheromone level (τ_o): 0.1 • Iterations: 250	• Number of fireflies: 30 • Light absorption coefficient (γ): 0.3 • Attractiveness (β_o): 0.7 • Randomness parameter (α): 0.25 • Iterations: 250

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Stage 3: Comparison of Process Parameter Optimization by PSO, ACO, and FA with GA

The PSO, ACO, and FA algorithms were coded and simulated using Python. To ensure adequate opportunity for convergence under uniform testing conditions, each algorithm was executed for 250 iterations. Common parameters such as population size, objective function, and stopping criteria were kept consistent across all algorithms to ensure a fair comparison. Parameter values were selected based on established literature and fine-tuned through preliminary testing to suit the problem context. Independent of 250 runs was performed to address the randomness inherent in these algorithms, and the average performance of *Ra* was computed and compared. This structured approach was followed to provide a balanced and objective evaluation of each algorithm's effectiveness.

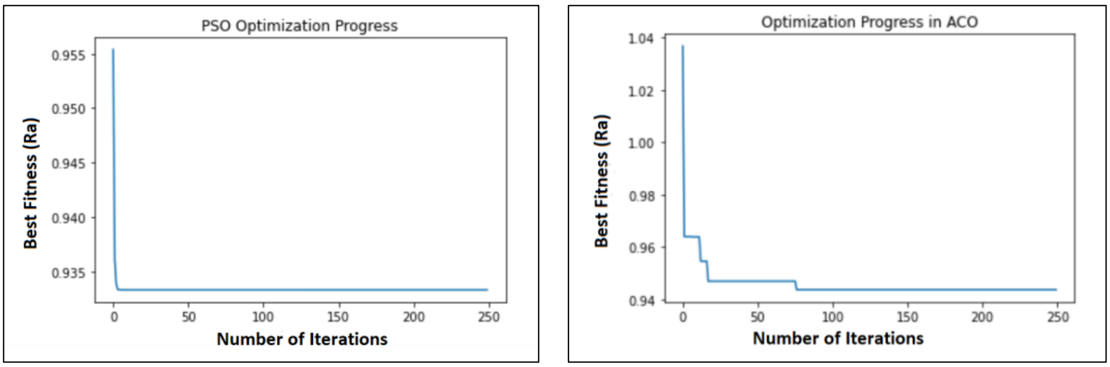
RESULTS AND DISCUSSION

The optimal process parameters such as, cutting speed, nitrogen gas pressure, and focal point location obtained from PSO, ACO, and FA simulations are presented in Table 3.

Table 3. Summary of the results of algorithms

Algorithm	Cutting speed (*X1*) mm/m	Nitrogen pressure (*X2*) bar	Focal point position (*X3*) mm	*Ra* in (µm)
GA (Tura et al., 2021)	2028.712	11.389	-2.499	0.9374
PSO	2000	11.4174	-2.5	0.9333
ACO	2078.7318	11.4480	-2.5	0.9437
FA	2097.3233	11.3282	-2.5	0.9449

The PSO algorithm began with a best fitness (minimum *Ra*) value of 0.955 µm and converged to 0.9333 µm by the second iteration, after which no further improvements were observed, as illustrated in Fig 1(a). In contrast, the ACO algorithm started with a best fitness (minimum *Ra*) value of 1.04 µm and achieved convergence at 0.9437 µm by the 75th iteration, with no subsequent enhancements, as shown in Fig 1(b). Similarly, the FA commenced with the best fitness (minimum *Ra*) value of 0.99 µm and converged to 0.9449 µm by the 20th iteration, after which no further improvements were noted, as depicted in Fig 1(c).



(a) (b)

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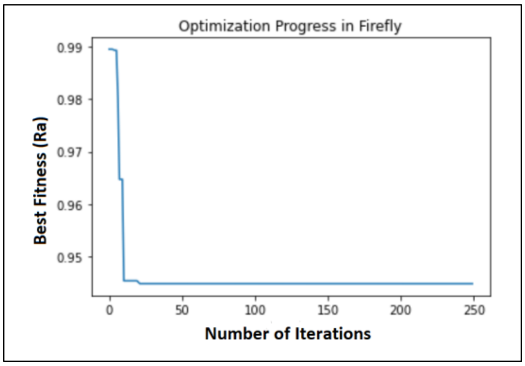

(c)

Fig. 1. Progress of optimization (a) PSO over the iteration (b) ACO over the iteration and (c) FA over the iteration.

Table 4. Simulation result of 250 runs

Algorithm	Minimum fitness	Maximum fitness	Mean	Standard deviation
PSO	0.9333	0.9838	0.9399	0.0171
ACO	0.9353	0.9986	0.9725	0.0143
FA	0.9335	0.9896	0.9538	0.0133

The results from 250 independent runs of the algorithms were analyzed using statistical methods to assess robustness and repeatability. Fig 2 and Fig 3 present the Z-score distributions, which indicate the degree of deviation of individual outcomes from the mean. The analysis indicates that the results for ACO and FA follow a normal distribution, while PSO results exhibit limited variation and do not conform to normality. The consistency of the PSO outcomes underscores its strong convergence stability. PSO algorithm demonstrated rapid convergence, reaching stable results within the first two iterations and maintaining them throughout all 250 iterations. *Ra* value of 0.9333 µm was observed in 217 runs, while a higher *Ra* value of 0.9838 µm was achieved in the remaining 33 runs. These two outcome groups are depicted in Fig 2. This consistency highlights PSO’s optimization capability and computational efficiency. Although normality tests are not emphasized due to the limited variance, the algorithm’s repeatable performance serves as a compelling indicator of its effectiveness under the defined parameter settings. Early and stable convergence contributes to reduced computational time without compromising solution quality.

While PSO's mean *Ra* value of 0.9399 µm is slightly better than ACO’s (0.9725 µm) and FA’s (0.9538 µm), it is important to consider the stability of these results. The standard deviations in Table 4 reveal that PSO has the highest variability (0.0171 µm), while ACO and FA show lower standard deviations (0.0143 µm and 0.0133 µm, respectively). This reveals that PSO, despite its slightly higher variation, can still achieve reliable and stable results across multiple runs. The relatively low standard deviations for all algorithms suggest that their performance is repeatable, and the differences observed in surface roughness values are statistically significant. While PSO clearly provides the best overall results in terms of surface roughness, its slightly higher variability (standard deviation) could be indicative of local search bias or insufficient global exploration in some instances.

The results from the ACO algorithm also follow a normal distribution but with a left skew. The analysis reveals a mean fitness value of 0.9725 µm and a standard deviation of 0.0143 µm. This left skew indicates that while most results cluster around the higher fitness values, some lower outliers are affecting the distribution. The results from the FA algorithm exhibit a right-skewed normal distribution. The analysis shows a mean fitness value of 0.9538 µm and a standard deviation of 0.0133 µm. This right skew suggests that while most results tend to be lower, some higher outliers are influencing the distribution.

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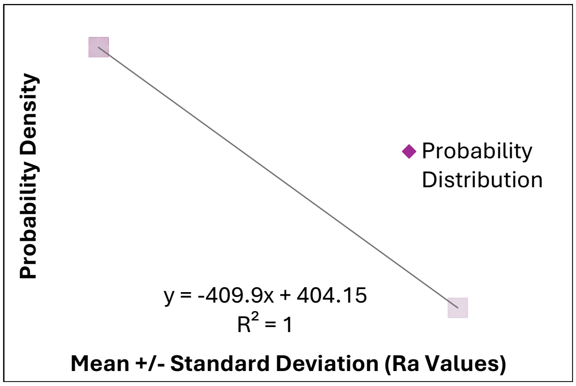
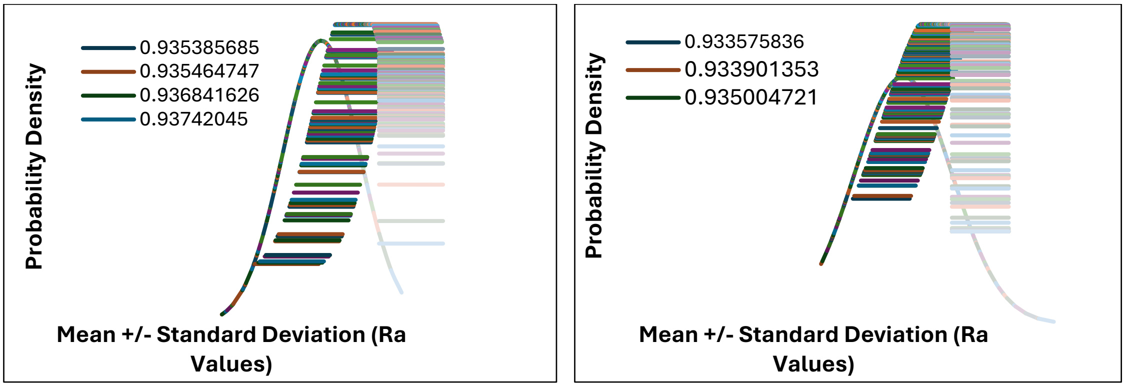


Fig. 2. Probability distribution for 250 runs of PSO.



(a) (b)

Fig. 3. Normal distribution curve for 250 runs (a) ACO and (b) FA.

The distribution of the fitness values for each algorithm, as illustrated in Fig 2 and Fig 3, strengthens the robustness of the findings. The normality of the data indicates that the results are not heavily skewed or biased, providing a more reliable foundation for comparisons. However, closer inspection of the skewness for ACO and FA algorithms reveals important nuances. ACO's left-skewed distribution suggests that although the algorithm tends to produce lower *Ra*, there are occasional lower values that could potentially indicate suboptimal performance in certain regions of the search space. FA's right-skewed distribution, on the other hand, suggests the opposite, a tendency for the algorithm to yield lower fitness values with occasional higher outliers. This may indicate that while FA can sometimes produce superior results, it is more prone to producing suboptimal solutions in the majority of runs.

CONCLUSION

The results presented offer a comparative analysis of three optimization algorithms, PSO, ACO, and FA focused on determining the optimal cutting parameters in nonconventional machining to minimize surface roughness (*Ra*). The PSO algorithm achieved a mean surface roughness of 0.9399 µm, outperforming the GA by 0.44% and with better convergence and repeatability compared to the ACO and FA algorithms. The ACO algorithm demonstrated a higher mean surface roughness of 0.9725 µm with a left-skewed normal distribution. The FA algorithm produced a mean surface roughness of 0.9538 µm, exhibiting a right-skewed

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normal distribution. This suggests a tendency to cluster around lower values with occasional higher outliers. The results of ACO and FA algorithm followed a normal distribution, which was confirmed through statistical analysis. The standard deviations (PSO: 0.0171 µm, ACO: 0.0143 µm, FA: 0.0133 µm) indicate that the PSO algorithm, while robust, exhibits slightly higher variability compared to the other two algorithms. However, the small standard deviation values for all algorithms suggest good repeatability. As shown in Fig 2 and Fig 3, the PSO algorithm achieves convergence by the second iteration, while the ACO and FA algorithms converge at the 75^{th} and 20^{th} iterations, respectively. PSO demonstrated strong repeatability, with fitness values consistently clustering around 0.9333 µm and 0.9838 µm across 250 runs, indicating stability. ACO showed slightly less consistency but maintained reliability with a broader fitness range. FA's right-skewed results suggest room for tuning to enhance consistency. PSO's rapid convergence and robust performance align with Baskar et al. (2012) and Xitian 's (2021) findings, which highlighted its success in achieving optimal cutting parameters. PSO converges faster than ACO and FA due to its velocity-based search mechanism, which enables particles to move directly toward optimal solutions. In contrast, ACO and FA rely on probabilistic decisions and indirect solution strategies. By employing structured learning to update positions, PSO achieves a balance between exploration and exploitation.

In summary, the findings demonstrate that the PSO algorithm not only converges rapidly but also yields the best results among the tested algorithms. The robustness and repeatability of the PSO algorithm are evident from the 250 run simulations. Future research could explore adaptive parameter tuning and self-adjusting control mechanisms to enhance algorithm efficiency. Evaluating these algorithms across diverse materials would demonstrate their effectiveness in varying machining environments. Comparative studies on machining processes like EDM and additive manufacturing could further validate their applicability.

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CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

AUTHORS' CONTRIBUTIONS

BVR contributed to conceptualization, software development, investigation, and interpretation of results. ARA was responsible for methodology, formal analysis, and validation. JSS handled writing of the original draft, as well as reviewing, editing, and referencing.

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