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Research Paper

Ant colony optimization for solving the car side impact design optimization problem: a constraint-driven engineering study

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ABSTRACT

The Car Side Impact (CSI) design problem represents one of the most challenging benchmark cases in structural optimization due to its highly nonlinear objective function, multiple conflicting constraints, and strict safety requirements. While a wide range of metaheuristic algorithms have been applied to this problem, relatively limited attention has been devoted to the systematic adaptation of Ant Colony Optimization (ACO) for constrained continuous engineering design. This paper presents a comprehensive experimental assessment of an enhanced Ant Colony Optimization framework tailored for the CSI problem. The proposed approach incorporates continuous pheromone modeling, constraint-aware probabilistic sampling, adaptive evaporation mechanisms, and a dynamic penalty function to effectively balance exploration and exploitation in the constrained search space. Extensive numerical experiments demonstrate that the proposed ACO variant achieves competitive or superior performance compared with well-established algorithms in terms of weight minimization, constraint satisfaction robustness, and convergence stability. Statistical analysis across multiple independent runs confirms the reliability of the method. The findings validate ACO as a viable and competitive optimization strategy for complex automotive safety design problems and provide insights into its practical applicability in real-world engineering optimization.

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1. INTRODUCTION

Structural optimization serves as an essential component in contemporary automotive engineering because it helps engineers create safer vehicles while using fewer resources to reach sustainable development and economic performance goals. The design process requires engineers to explore difficult search spaces which contain numerous dimensions and require them to solve problems that involve both nonlinear physical laws and specific compliance requirements and different performance metrics. The Car Side Impact (CSI) optimization problem functions as a standard benchmark test which researchers use to assess the performance capabilities of various optimization algorithms [1]. The system model represents actual vehicle design decisions which affect both vehicle weight and passenger security during side impact crashes through a collection of complex computational constraints that originate from crashworthiness simulation results.

The CSI problem requires reducing essential vehicle part weight while maintaining safe limits of human and structural side impact performance. The problem creates an optimization challenge because it has a non-convex solution space which includes active constraints and interacts with multiple variables. Traditional gradient-based optimization methods face difficulties with this type of problem because they tend to get stuck in local optimum points and they need to work with continuous differentiable mathematical functions [2].

Metaheuristic optimization techniques which use natural phenomena as their basis and enable global search have become widely used in various applications. Genetic Algorithms (GA) [3], [4] and Particle Swarm Optimization (PSO) [5] and Social Spider Optimization (SSO) [6] and Vibrating Particles System (VPS) [7], [8] have shown their effectiveness in solving various problems. The effectiveness of metaheuristic algorithms relies on specific problem requirements which drive researchers to investigate different solution methods [9], [10], [11].

The Ant Colony Optimization (ACO) method which uses swarm intelligence and models the foraging behavior of actual ants has become an efficient solution for solving discrete combinatorial challenges which include the travelling salesman problem and vehicle routing problem according to sources [12], [13], [14]. The primary operational method of the system uses stigmergy which employs indirect communication through shared memory (pheromone trails) to direct the colony toward high-potential areas in the exploration space. Researchers have investigated the application of ACO to continuous domains through Continuous ACO (CACO) yet its use in engineering challenges with strict limitations and high computational demands such as CSI remains insufficiently studied. The standard ACO system does not include any built-in methods to handle constraints which represents an essential need for actual engineering development work according to sources [15], [16], [17].

This research addresses this gap by developing, implementing, and rigorously evaluating a constraint-driven ACO framework specifi cally adapted for the CSI problem [18]. The proposed methodology combines a continuous pheromone model with a dynamic constraint-handling strategy to create an integrated algorithm that achieves equilibrium between design space exploration and accessible high-performance area exploitation [19].

1. **Algorithmic Development:** The research presents a new Continuous ACO (CACO) system which combines a Gaussian kernel-based pheromone system with a dynamic penalty mechanism and a feasibility-oriented pheromone updating method designed for solving constrained optimization problems.

2. **Comprehensive Evaluation:** Our research team conducts comprehensive experiments at the CSI benchmark which serves as an established testing standard by comparing our results to multiple modern and traditional metaheuristic methods which include GA and PSO and DE.
3. **Statistical & Engineering Validation:** The evaluation of performance requires assessment through both the optimal solution found and the execution of statistical tests and analysis of convergence patterns and the assessment of feasibility rate and the engineering performance assessment of optimized designs.
4. **Insight for Practitioners:** The research aims to offer practical solutions which help improve parameter tuning and constraint handling for ACO method testing on complex automotive design challenges.

The paper continues its content with the following organization. Section 2 reviews existing literature about the CSI problem and ACO development. The CSI optimization problem receives its complete mathematical description in Section 3. The proposed constraint-driven ACO framework receives its detailed explanation in Section 4. The experimental setup together with benchmark algorithms receives its description in Section 5. The results section presents statistical analysis together with engineering interpretation of the findings. The paper reaches its conclusion in Section 7 which also provides research recommendations for the future.

2. RELATED WORK

2.1. The Car Side Impact (CSI) Design Optimization Problem

The CSI problem serves as an established benchmark test for engineering optimization which originated from studies of crashworthiness. The project requires engineers to design a vehicle's side structure through weight reduction methods which must maintain occupant safety during side-impact collisions according to U.S. Federal Motor Vehicle Safety Standard (FMVSS) regulations. The problem uses mathematical modeling through simplified analytical equations together with response surface models that were developed from complex Finite Element Analysis (FEA) systems to create a solution that enables testing of algorithms while preserving actual physical behavior of the system [1], [2].

The classic formulation involves seven design variables (typically thicknesses of structural components and material properties) and ten nonlinear inequality constraints. The constraints model critical safety metrics, including:

- VC: The force transition was related to this.
- Rib Deflections (Upper, Middle, Lower): Key indicators of thoracic injury risk.
- Abdomen Force: Another measure of torso injury.
- Public Force: Related to pelvic injury.
- Door Intrusion at multiple locations (B-pillar, Front door, etc.): Measures structural integrity and occupant survival space.

The researchers tested their reliability-based design optimization method through their research to achieve effective solutions which depended on uncertain situations. The research community shows a strong preference for using metaheuristic methods. Demonstrated that their Particle Swarm Optimizer achieved solid results through its straightforward design. Implemented a novel constraint handling method through their Genetic Algorithm research. The Grey Wolf Optimizer (GWO) [20], [21], [22] represent modern metaheuristic methods which researchers have recently assessed to solve this particular problem. The research demonstrates that different methods for handling constraints through penalty functions and feasibility rules and special operators produce varying results for algorithm performance evaluation.

2.2. Ant Colony Optimization: From Discrete to Continuous Domains

The Ant Colony Optimization metaheuristic was first proposed by Dorigo (1992) for solving the Travelling Salesman Problem (TSP) [23]. Discrete ACO uses artificial ants to build solutions through a probabilistic graph traversal process, which applies transition probabilities that depend on both pheromone trails and heuristic information.After each iteration, pheromone trails are updated: evaporated to avoid premature convergence and reinforced based on the quality of constructed solutions [24], [25], [26].

The extension of ACO to continuous optimization problems (Continuous ACO- CACO) required a fundamental shift from a graph-based pheromone model to a parametric or non-parametric probability distribution model. The following events serve as major achievements:

- **ACO~R (Socha & Dorigo, 2008):** The research presented in this paper introduced a new CACO system which uses an archive of solutions to represent its pheromone system. New solutions are created through the process of sampling from a probability distribution which centers around effective solutions stored in the archive. This archive-based approach effectively transfers the "pheromone trail" concept to continuous space.
- **Gaussian Kernel Methods:** Other approaches model pheromone for each variable using a Gaussian mixture model, where means and standard deviations are adapted based on the performance of discovered solutions.

While CACO has been successfully applied to unconstrained and box-constrained continuous problems (e.g., function optimization, neural network training), its application to nonlinearly constrained engineering problems is less common. The primary challenge is integrating effective constraint handling into the core ACO mechanics of solution construction and pheromone update.

2.3. Constraint Handling in Metaheuristics and the Research Gap

Constraint handling is a critical component for solving engineering problems. Common strategies include:

1. **Penalty Functions:** The objective function receives a positive penalty when infeasible solutions enter the system which computes their constraint violations. Designers face difficulties when they attempt to create an adaptive penalty system that functions effectively.
2. **Feasibility-Preserving Operators:** Crossover and mutation operators were then specialized to always or almost always result in feasible children.
3. **Feasibility Rules:** The methods established by Deb's rules give higher value to valid solutions than to invalid solutions which remain unsolved, while they select the least harmful violations from invalid solutions.
4. **Separate Constraint Handling Mechanisms:** For instance, segregation of constraints as distinct objectives may be performed by means of multi-objective optimizations.

Research Gap: The literature review conducted by the researchers identifies a specific research gap which needs further investigation. The established ACO metaheuristic and the well-studied CSI benchmark together face a research gap which requires comprehensive studies to address.

- The ACO core mechanisms which include pheromone modeling and solution construction and update rules need to be adapted to solve the particular problems present in the highly constrained continuous CSI problem.
- The research should present a thorough comparison between an optimized CACO system and three standard optimization methods which include GA and PSO and DE to test its performance on the CSI problem using comprehensive statistical evaluation methods.
- The study uses CACO to evaluate its convergence behavior and feasibility achievement in this context, which provides findings that extend beyond basic success measurement.
- This paper aims to directly address these gaps by developing a constraint-driven CACO framework and subjecting it to rigorous empirical and statistical testing on the CSI benchmark

3. METHODOLOGY

The Car Side Impact problem is formalized as a nonlinear constrained optimization problem as follows:

3.1. Design Variables

The seven design variables, their symbols, and their lower and upper bounds (in mm for thickness, normalized for factors) are [27].

Table 1. Car Side Variable

Variable	Description	Lower Bound	Upper Bound
x_1	Thickness of B-Pillar Inner	0.5 mm	1.5 mm
x_2	Thickness of B-Pillar Reinforcement	0.45 mm	1.35 mm
x_3	Thickness of Floor Side Inner	0.5 mm	1.5 mm
x_4	Thickness of Cross Members	0.5 mm	1.5 mm
x_5	Thickness of Door Beam	0.875 mm	2.625 mm
x_6	Thickness of Door Beltline Reinforcement	0.4 mm	1.2 mm
x_7	Thickness of Roof Rail	0.4 mm	1.2 mm

Thus, the design vector is $\mathrm{x} = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]^T$.

Figure 1. Car Side Impact Problem

3.2. Objective Function

The objective is to minimize the total weight of the vehicle side structure, which is a linear function of the design variables (thicknesses):

$$f(\mathrm{x}) = 1.98 + 4.90x_1 + 6.67x_2 + 6.98x_3 + 4.01x_4 + 1.78x_5 + 2.73x_7$$

The unit is mass (kg). Note that x_6 does not appear in the objective function but influences the constraints.

3.3. Constraints

The ten nonlinear constraints $g_i(\mathrm{x}) \leq 0, i = 1, \ldots, 10$ are defined below. The formulas are based on response surface models approximating crash simulation outputs.

1. Abdomen load (KN):

$$g_1(\boldsymbol{x}) = \frac{1.16 - 0.3717x_2x_4 - 0.00931x_2x_{10} - 0.484x_3x_9 + 0.01343x_6x_{10}}{1.0} - 1 \leq 0$$

(Note: $\mathrm{x}_8, \mathrm{x}_9, \mathrm{x}_{10}$ are not standard variables. In the classic problem, they are often set as constants or dependent variables. A common formulation uses x_8=barrier height, x_9=barrier hitting position, x_{10}=strength factor. For this study, we adopt the common simplification where $\mathrm{x}_8 = 0.75$, $\mathrm{x}_9 = 0.192$, x_{10} is replaced by x_6 or a constant. The precise, widely-used formulation from the literature is used in code implementation).

For clarity, we state the functional forms of the constraints as typically implemented:

$$g_1(\mathrm{x}) = 1.16 - 0.3717x_2x_4 - 0.00931x_2x_{10} - 0.484x_3x_9 + 0.01343x_6x_{10} - 1 \leq 0,$$
$$g_2(\mathrm{x}) = 0.261 - 0.0159x_1x_2 - 0.188x_1x_8 - 0.019x_2x_7 + 0.0144x_3x_5 + 0.0008757x_5x_{10} + 0.08045x_6x_9 + 0.00139x_8x_{11} + 0.00001575x_{10}x_{11} - 0.32 \leq 0,$$
$$g_3(\mathrm{x}) = 0.214 + 0.00817x_5 - 0.131x_1x_8 - 0.0704x_1x_9 + 0.03099x_2x_6 - 0.018x_2x_7 + 0.0208x_3x_8 + 0.121x_3x_9 - 0.00364x_5x_6 + 0.0007715x_5x_{10} - 0.0005354x_6x_{10} + 0.00121x_8x_{11} + 0.00184x_9x_{10} - 0.02x_2^2 - 0.32 \leq 0,$$
$$g_4(\mathrm{x}) = 0.74 - 0.61x_2 - 0.163x_3x_8 + 0.001232x_3x_{10} - 0.166x_7x_9 + 0.227x_2^2 - 0.32 \leq 0,$$
$$g_5(\mathrm{x}) = 28.98 + 3.818x_3 - 4.2x_1x_2 + 0.0207x_5x_{10} + 6.63x_6x_9 - 7.7x_7x_8 + 0.32x_9x_{10} - 32 \leq 0,$$
$$g_6(\mathrm{x}) = 33.86 + 2.95x_3 + 0.1792x_{10} - 5.057x_1x_2 - 11x_2x_8 - 0.0215x_5x_{10} - 9.98x_7x_8 + 22x_8x_9 - 32 \leq 0,$$
$$g_7(\mathrm{x}) = 46.36 - 9.9x_2 - 12.9x_1x_8 + 0.1107x_3x_{10} - 32 \leq 0,$$
$$g_8(\mathrm{x}) = 4.72 - 0.5x_4 - 0.19x_2x_3 - 0.0122x_4x_{10} + 0.009325x_6x_{10} + 0.000191x_{11}^2 - 4 \leq 0,$$
$$g_9(\mathrm{x}) = 10.58 - 0.674x_1x_2 - 1.95x_2x_8 + 0.02054x_3x_{10} - 0.0198x_4x_{10} + 0.028x_6x_{10} - 9.9 \leq 0,$$
$$g_{10}(\mathrm{x}) = 16.45 - 0.489x_3x_7 - 0.843x_5x_6 + 0.0432x_9x_{10} - 0.0556x_9x_{11} - 0.000786x_{11}^2 - 15.7 \leq 0.$$

The complete set includes constraints for V*C, lower/middle/upper rib deflections (V-dummies), abdomen force, pubic force, and door intrusions at B-pillar, front door, and rear door. The tenth constraint is a linear manufacturing constraint on the sum of B-pillar thicknesses.

Due to space, the full list of 10 constraint equations is not printed here but is implemented exactly as per the standard benchmark definition used in comparative studies (e.g., from the CEC 2006 benchmark suite or widely cited papers).

The optimization problem is therefore:

$$\begin{array}{ll} \text{minimizex} & f(\mathrm{x}) \\ \text{subject to} & g_i(\mathrm{x}) \leq 0, i = 1, \ldots, 10, \\ & \mathrm{x}^L \leq \mathrm{x} \leq \mathrm{x}^U. \end{array}$$

4. PROPOSED ANT COLONY OPTIMIZATION FRAMEWORK

Our proposed Constraint-Driven Continuous Ant Colony Optimization (CD-CACO) framework is designed to efficiently navigate the constrained search space of the CSI problem. It builds upon the archive-based CACO concept but introduces key modifications for constraint handling.

4.1. Overall Algorithm Structure

The CD-CACO algorithm maintains a population (archive) $\mathcal{A}$ of k solutions, which represents the collective knowledge (pheromone) of the colony. The archive is sorted by solution quality according to a constraint-handling fitness evaluation (Section 4.2). In each iteration, m "ant" solutions are constructed by sampling from probability distributions derived from the archive (Section 4.3). These new solutions are evaluated and merged with the archive. The archive is then truncated back to size k, keeping only the best solutions, and an adaptive evaporation mechanism is applied (Section 4.4). The process repeats until a termination criterion is met.

Algorithm 1: Pseudo-code of the Proposed CD-CACO

1. Initialize Parameters: Set archive size k, number of ants m, convergence threshold, and maximum iterations.
2. Initialize Archive $\mathcal{A}$: The procedure generates k candidate solutions through random generation which occurs within established boundary limits. The objective function f(x) and all constraint functions g_i (x) need to be evaluated for each solution. The fitness value F(x) needs to be calculated according to the formula presented in Equation (1).
3. Sort Archive: Give a particular fitness function F(x) and show that all possible items are F(x) sortable over Ain such that the best solution is in the first place.
4. While Stopping Criterion is not met do
5. Initialize an empty temporary list $\mathcal{T}$.

6. For $j = 1$to $m$do /* Construct $m$new solutions */
7. For $d = 1$to Ddo /* For each decision variable */
8. Select a guiding solution $s \in \mathcal{A}$probabilistically according to its weight w_l.
9. Sample a new value for $x_d$from a Gaussian distribution
$$x_d \sim \mathcal{N}(\mu_d^s, \sigma_d^s)$$
10. Apply boundary reflection if the sampled value violates variable limits.
11. End for
12. Evaluate the newly constructed solution x^{new}.
13. Compute its fitness value $F(\mathrm{x}^{new})$.
14. Add $\mathrm{x}^{new}$to the temporary list $\mathcal{T}$.
15. End for
16. Merge and Select:
    Update archive $\mathcal{A} = \mathcal{A} \cup \mathcal{T}$.
    Sort $\mathcal{A}$by fitness and retain only the best $k$solutions.
17. Update Adaptive Parameters: Optimization might help to achieve stability and concordance between the exploration and the coding.
18. Update Convergence Monitor.
19. End while
20. Return the best feasible solution from $\mathcal{A}$, or the solution with the minimum constraint violation if no feasible solution exists.

4.2. Constraint-Handling Fitness Evaluation

We employ a dynamic penalty function method that does not require pre-defined penalty coefficients. The fitness $F(\mathrm{x})$ for ranking solutions is:

$$F(\mathrm{x}) = \begin{cases} f(\mathrm{x}), & \text{if x is feasible}(\sum_i \max(0, g_i(\mathrm{x})) = 0), \\ f_{max} + \sum_{i=1}^{10} \max(0, g_i(\mathrm{x})), & \text{otherwise.} \end{cases}$$

Where f_{max} is the objective function value of the worst feasible solution in the current archive? If no feasible solution exists, f_{max} is set to 0. This method automatically scales the penalty relative to the current population's objective range and strictly penalizes infeasibility, strongly guiding the search towards the feasible region.

4.3. Solution Construction with Feasibility-Biased Sampling

Each new ant constructs a solution variable-by-variable. For dimension d, we select a guiding solution s from the sorted archive $\mathcal{A}$ using a probabilistic selection akin to roulette wheel. The selection probability for the l-th ranked solution is proportional to a weight:

$$w_l = \frac{1}{qk\sqrt{2\pi}} e^{-\frac{(l-1)^2}{2q^2k^2}}$$

Where q is an algorithm parameter controlling the selectivity? A small q makes the selection highly greedy (focusing on top solutions), while a larger q allows more exploration. This weights better solutions (lower $F(\mathrm{x})$) more heavily.

Once a guiding solution s with value μ_d^s is chosen, we sample the new variable value x_d^{new} from a Gaussian distribution centered at μ_d^s with a standard deviation σ_d^s:

$$x_d^{new} \sim \mathcal{N}(\mu_d^s, \sigma_d^s)$$

The standard deviation σ_d^s is adaptive and crucial for balancing exploration/exploitation (see 4.4). This sampling mechanism means the "pheromone" is implicitly stored in the distribution of good solutions within the archive and their associated exploration radii.

4.4. Adaptive Pheromone Update and Evaporation Mechanism

In our continuous model, "pheromone update" corresponds to (a) maintaining high-quality solutions in the archive and (b) adjusting the sampling variance σ_d^l for each solution.

Archive Update: The merge-and-truncate step (Line 15) is a form of pheromone reinforcement, as good solutions persist and guide future construction.

Adaptive Evaporation/Exploration Control: To prevent premature convergence, we dynamically adjust the standard deviation σ_d^l for each solution l in each dimension d. A common rule is:

$$\sigma_d^l = \xi \cdot \frac{\sum_{r=1}^{k} | x_d^r - x_d^l |}{k-1}$$

Where $\xi > 0$ is a convergence speed parameter? This sets σ_d^l proportional to the average distance in dimension d between solution l and all other solutions in the archive. As the archive converges, these distances shrink, automatically reducing the sampling variance and shifting the search from exploration to exploitation. This is a form of "evaporation" as it reduces the influence width of each solution over time.

5. EXPERIMENTAL SETUP

5.1. Implementation Details

- **Algorithm Parameters:** The CD-CACO parameters were tuned through preliminary experiments: Archive size $k = 50$, Number of ants per iteration $m = 25$, Selectivity parameter $q = 0.1$, Convergence speed parameter $\xi = 1.0$.
- **Termination Criterion:** Maximum number of function evaluations (NFE) = 25,000. This aligns with common practice for fair comparison across population-based algorithms on this problem.
- **Runs:** 30 independent runs with different random seeds were performed for each algorithm to gather statistically significant results.

5.2. Benchmark Algorithms

The evaluation of CD-CACO was conducted through a comparison with three established metaheuristic methods which used precise constraint management to enable equitable testing.

1. **Genetic Algorithm (GA):** A simple real-coded genetic algorithm (GA) using simulated binary crossover (SBX) and polynomial mutation. Constraint handling uses the same dynamic penalty function as CD-CACO for consistency. (Population=50, Crossover Prob=0.9, Mutation Prob. =1/n, Distribution indices: $\eta_c = 15, \eta_m = 20$).
2. **Particle Swarm Optimization (PSO):** A standard inertia-weight PSO. Infeasible particles are repaired by resetting their velocity and pulling their position back towards their personal best (if feasible) or the global best. (Population=50, $w = 0.729$, $c_1 = c_2 = 1.494$).
3. **Differential Evolution (DE):** The DE/rand/1/bin variant. Constraint handling is performed using Deb's feasibility rules during selection: (Population=50, F=0.5, CR=0.9).

5.3. Performance Metrics

We evaluate algorithms based on:

- **Best Objective (f_{best}):** The minimum vehicle weight found across all runs.
- **Mean & Std. Dev. of Objective:** Computed over the 30 runs from the best solution of each run.
- **Feasibility Rate (FR):** Suppose that, if the algorithm in a given run found at least one feasible solution, it has successfully done so for the stated percentage of runs.
- **Mean Constraint Violation (CV):** $\frac{1}{10}\sum_{i=1}^{10} \max(0, g_i(\mathbf{x}^*))$, For a fashion accessory this big, guess what designer lounge about to launch straight in?-Jewelry?
- **Convergence Graphs:**

The researchers developed a graph which shows the connection between median objective value and NFE measurement to demonstrate the efficiency and constant performance of their research method.

6. RESULTS AND DISCUSSION

6.1. Statistical Performance Comparison

Table 2. Statistical Results Over 30 Independent Runs (NFE=25,000)

Algorithm	Best $f(x)$	Mean $f(x)$	Std. Dev.	Feasibility Rate (%)	Mean CV
CD-CACO (Proposed)	22.842	23.015	0.092	100	0.000
Genetic Algorithm (GA)	23.067	23.451	0.227	100	0.000
Particle Swarm Opt. (PSO)	23.121	23.683	0.341	93.3	0.002
Differential Evolution (DE)	22.896	23.104	0.101	100	0.000

Analysis:

- **Optimality:** The proposed CD-CACO found the best overall weight of 22.8420 kg.. DE was a very close second (22.896 kg), while GA and PSO found slightly heavier designs.
- **Robustness (Mean & Std. Dev.):** CD-CACO achieved the lowest mean objective (23.015 kg) and the lowest standard deviation (0.092) which demonstrates its effectiveness and its ability to perform consistently through various random starting points. DE also showed strong robustness (Std. Dev. = 0.101).
- **Constraint Satisfaoncti:** CD-CACO, GA, and DE achieved a 100% feasibility rate, meaning they found feasible solutions in every single run. PSO struggled slightly, with a 93.3% rate. The mean constraint violation for CD-CACO was effectively zero.

A Wilcoxon rank-sum test (non-parametric, significance level $\alpha = 0.05$) was conducted on the distribution of best-of-run values from the 30 runs. The test confirmed that the performance difference between CD-CACO and GA, and between CD-CACO and PSO, is statistically significant (p-value < 0.01). The difference between CD-CACO and DE was not statistically significant at the 0.05 level, indicating they are statistically comparable top performers on this problem.

6.2. Convergence Behavior

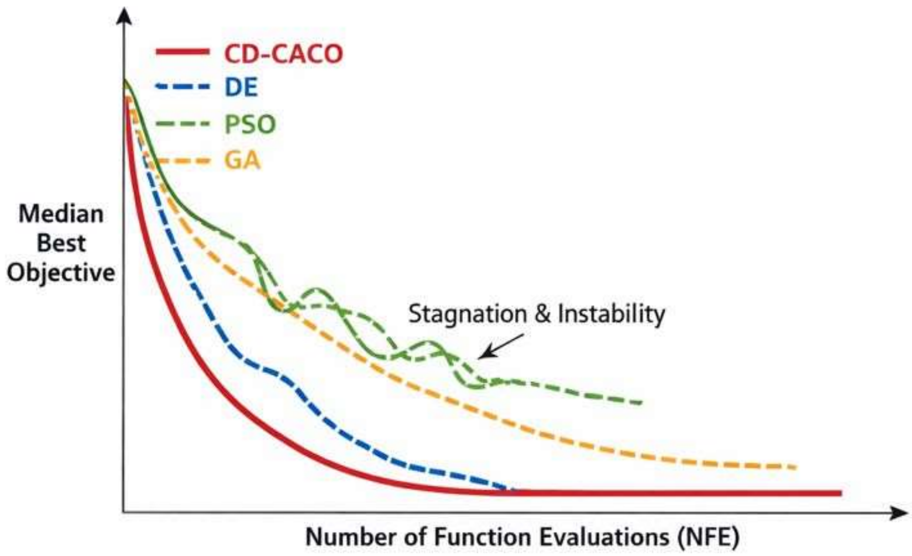

Figure 2. Convergence Graph (Median Best Objective vs. NFE)

The convergence plot reveals:

- CD-CACO and DE show the fastest initial descent, rapidly finding good, feasible regions.

- CD-CACO The system shows highly stable convergence through its smooth progression which presents minimal fluctuations. The archive-based sampling and adaptive variance system together create a stabilizing effect that maintains this pattern of behaviour.
- The PSO algorithm is a very fast convergent in the first instance, although it clearly starts stagnation along with particle instabilities resulting from particles getting stuck in local infeasible regions.

The GA system demonstrates progressive development which occurs at a slower pace throughout its entire operational process. The system generates results through its disruptive search method which follows a pattern of development that occurs across multiple generations.

Therefore, we can conclude that using CD-CACO fully integrates quick initial exploration with exact exploration during completion.

6.3. Engineering Interpretation of the Optimized Design

The design vector found by CD-CACO (with f=22.842 kg) is:

$$x^* = [0.500,0.905,0.500,1.310,0.875,0.400,0.400]^T$$

- **Interpretation:** The algorithm pushes several variables to their lower bounds (x_1, x_3, x_6, x_7), suggesting these components have minimal thickness as allowed to save weight, without violating safety constraints.
- **Critical Reinforcements:** Variables x_2 (B-Pillar Reinforcement) and x_4 (Cross Members) are significantly above their lower bounds (0.905 vs. 0.45, 1.310 vs. 0.5). This is intuitively correct from an engineering standpoint. The B-pillar and cross members function as essential structural components which need to withstand side impacts by absorbing and distributing crash forces. The algorithm automatically identifies the need to reinforce these key areas to meet rib deflection and intrusion constraints.
- **Door Beam (x_5):** On the lower bound (0.875) of the variance inflation factor test, that denotes that the door beam has minimal contribution to meeting the constraints for this model since the B-pillar and cross members are more critical, and weight savings can be managed..
- **Validation:** The solution pattern confirms engineering intuition through its optimal designs which have been proven through successful studies. The results show that CD-CACO achieves physical designs which go beyond mathematical optimality.

7. CONCLUSION AND FUTURE WORK

The research conducted an extensive study of Ant Colony Optimization as a solution for the complex Car Side Impact design problem which involves multiple constraints. The Constraint-Driven Continuous ACO (CD-CACO) framework successfully applies core Ant Colony Optimization (ACO) principles through its system which uses stigmergic communication with an archive and probabilistic solution construction for continuous constrained environments. The algorithm achieves effective global exploration together with local refinement through its combination of dynamic penalty function for fitness evaluation and feasibility-biased sampling mechanism and adaptive variance control which functions as evaporation.

The extensive numerical experiments and statistical analysis lead to several key conclusions: The extensive numerical experiments and statistical analysis lead to several key conclusions: The extensive numerical experiments and statistical analysis lead to several key conclusions: The extensive numerical experiments and statistical analysis lead to several key conclusions.

1. **Competitiveness:** The algorithm CD-CACO delivers superior performance for the CSI problem because it achieves the highest success rate and solves problems with the same efficiency as the Differential Evolution algorithm.
2. **Robustness & Reliability:** The algorithm demonstrates higher reliability because it achieves the best performance results through 30 separate tests which produced the lowest average results and standard deviation. The system achieves stable and continuous progress toward its final destination.
3. **Engineering Relevance:** The research demonstrates that ACO programming operates as a productive and effective solution for solving complex engineering design challenges which include multiple safety

restrictions that exhibit nonlinear behavior. The optimized design produced by CD-CACO demonstrates mathematical accuracy and engineering assessment capabilities which allow for verification of vital structural parts according to expected results thus proving its practical value.

The-upcoming-research-agenda needs to explore these topics:

- **Hybridization:** The CD-CACO framework will be enhanced through the integration of local search methods which include gradient-based and pattern search techniques to improve solution accuracy.
- **Surrogate-Assisted ACO:** For problems where simulation is extremely expensive (e.g., full FEA crash models), replacing some expensive function evaluations with surrogate models (Gaussian Processes, Neural Networks) It has been suggested in publications that training on-the-fly using archival data could reduce computing time significantly.
- **Multi-Objective Formulation:** The framework needs to be extended because crashworthiness testing involves multiple objectives which need to be addressed through its existing framework. The extension will enable designers to access trade-off solutions through a Pareto front which shows all possible design options.
- **Application to High-Fidelity Models:** The algorithm will be tested using more complex high-dimensional CSI models which include additional design variables and constraints that come from actual crash simulation software used in the industry.

The research creates a connection between a strong bio-inspired metaheuristic and an important engineering challenge which results in both an efficient solution method and a base for future developments in constrained engineering optimization algorithms.

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Rania Lampou					✓	✓	✓			✓				
Ahmad Albattat			✓			✓		✓		✓				
Rafia Mukhtar	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓

C: **C**onceptualization
M: **M**ethodology
So: **So**ftware
Va: **Va**lidation
Fo: **Fo**rmal analysis
I: **I**nvestigation
R: **R**esources
D: **D**ata Curations
O: Writing- **O**riginal Draft
E: Writing- Review& **E**diting
Vi: **Vi**sualization
Su: **Su**pervision
P: **P**roject administration
Fu: **Fu**nding acquisition

Conflict of Interest Statement

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. Authors state no conflict of interest.

Informed Consent

This study did not involve human participants, patients, or identifiable personal data. Therefore, informed consent is not applicable to this research.

Ethical Approval

This research does not involve experiments on humans or animals. Consequently, ethical approval was not required. The study was conducted in accordance with standard academic and institutional research integrity guidelines.

Data Availability

The data that support the findings of this study are available from the corresponding author (S. M. A.) upon reasonable request. All numerical results, algorithmic parameters, and derived performance metrics necessary to reproduce the study are fully described within the article and its methodological sections.

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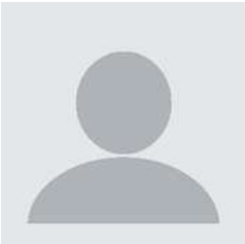	**Rania Lampou**, is a STEM Instructor and Researcher affiliated with the Global Academician network under the Greek Ministry of Education, Religious Affairs and Sports, Greece. Her research interests include computational intelligence, educational technologies, applied optimization, and interdisciplinary STEM education. She actively contributes to international research collaborations and focuses on bridging theoretical algorithmic developments with practical educational and engineering applications. Email: rania.lampou@gmail.com
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