Testing for Welding, Joining or Additive Manufacturing

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Enhanced crash performance of multi-cell crash box for electric vehicle battery pack design

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Abstract: This paper is dedicated to enhancing the crash performance of a PA6 GF30 multicell crash box used for the crashworthiness and safety of the battery pack system used in electric vehicles. In this paper, a new hybrid optimization algorithm (HSFOA) combining the starfish optimization algorithm, dynamic oppositional-based learning, and a piecewise chaotic map is proposed, and a novel PA6 GF30 composite multicell crash box is developed to protect the electric vehicle battery pack. The performance of HSFOA is validated by applying it to piston rod design, car collision study, welded beam design, and truss structure optimization. After validation, the HSFOA is used to optimize a multicell energy absorber to evaluate its effectiveness in enhancing energy dissipation during collisions of electric vehicle battery pack. The developed crash box design, via finite element analysis and hybrid starfish optimization method, is manufactured by 3D printing and subjected to dynamic impact tests to validate crash performance. The results revealed that the developed design exhibited the highest crash performances, which are comparable to each other. Additionally, the PA6-Gf30 material for the developed multicell crash box, and HSFOA perform well in terms of efficiency, convergence, and stability in polymer-based electric vehicle battery pack design.

Keywords: hybrid starfish algorithm; composite; electric vehicle; battery case; dynamic oppositional-based learning; piecewise chaotic map

1 Introduction

In recent years, the increasing number of different types of vehicles has led to a significant rise in traffic accidents. This situation has necessitated the development of passive safety systems aimed at enhancing the safety of both drivers and passengers. In the automotive industry, energy-absorbing systems are expected to be lightweight, capable of high energy absorption, and easy to manufacture. Studies have highlighted the potential of conical, triggered, and corrugated tubes, thin-walled structures, and composite materials in this context. Although traditional materials such as steel and aluminum have been widely used, composite materials have gained attention in recent years due to their high strength and low weight. However, producing multicell structures using composites is challenging; thus, they are often used as reinforcing elements. Researchers have started using additive manufacturing (AM) technologies to overcome this limitation and produce multicell crash boxes from composite materials.

Optimization algorithms have a vital tool in solving challenging and constrained problems. For many years, design industries have focused on the optimized and highly efficient design of various systems, including the automobile industry, the thermal industry, and engineering-discipline organizations. Various systems were optimized using researchers' classical optimization techniques. However, the multimodal nature of the problems, critical constraints, and computational efficiency are some of the major demerits. To overcome this, nature-inspired algorithms, called metaheuristics (MHs), were developed to mimic or be inspired by each system of nature [1]–[3]. For instance, Figure 1 gives an idea about inspirational sources and the most recently developed MH optimizers [3]. These MH optimizers were applied over various applications due to their effective convergence rate, less computational time, potential convergence, and diversity trends [4]–[12].

Moreover, as the complexity of the problem increases, MHs in critically constraining problems realize a local optima trap, a lower convergence rate, and an imbalance between exploration and exploitation phases. To overcome the state challenges, several modifications have been incorporated into the base algorithm. For instance, a dynamic oppositional learning technique [13] that improves the exploitation phase of the algorithm, piecewise chaotic maps

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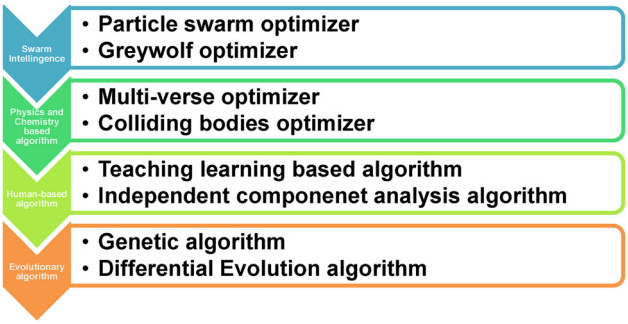


Figure 1: Classical state-of-the-art optimizers and their subclasses.

that enhance the exploration phase [14], Levy flight mechanisms that improve the balance between the two phases, and hybrid algorithms that utilize better portions from each of the considered algorithms [15]. Apart from this, the solution to the design problems, especially truss structures and complex manufacturing problems consisting of multiple fitness functions, is realized by multiobjective optimizers [16]–[20]. Apart from this, a wide range of applications were identified in the literature that applied the MHs algorithm to optimize various parameters. Furthermore, electrical discharge machining process parameters [21], solar photovoltaic parameters [22], automobile system components [23], truss structures [24], fuzzy logic circuits [25], robotic arms [26], mechanical engineering components [27], and medical field applications [28]. Moreover, the effectiveness of the optimizer is proliferating by augmenting the machine learning techniques, the ANN technique (artificial neural network), and artificial intelligence techniques [29]. This being said, the research domain of MHs provides a superior objective to optimize the existing systems further by enhancing the efficiency of the existing algorithms. In the present article, a newly developed algorithm named Starfish Optimizer (SFO) is being enhanced with the dynamic oppositional-based technique and piecewise chaotic map to solve the various design engineering components. The starfish optimizer is based on the techniques of prey trapping, food foraging, and starfish survival, which are generally identified in the deep ocean. Accordingly, various statistical results attained by the modified algorithms were compared with those reported in the literature of well-known optimizers.

Energy absorbers are one of the key components for improving the crash performance of electric vehicle battery enclosures [30]–[44].

Polymer-based composite materials have attracted significant attention in recent years due to their lightweight nature, corrosion resistance, and high specific strength [37]. Among these, PA6 GF30 (polyamide 6 reinforced with 30 % glass fiber) stands out as an important option for structural applications. In addition to PA6 GF30, materials such as carbon fiber–reinforced polyamides and glass fiber–filled polypropylene are also widely investigated for energy absorption applications. These materials are particularly relevant in the automotive industry, where reducing vehicle weight while maintaining crash safety is a key design challenge.

This study focuses on the design, optimization, and experimental evaluation of multicell energy absorbers produced with polymer composites using additive manufacturing techniques. In this study, multicell energy absorbers were designed and manufactured using PA6 GF30 filaments through the fused deposition modeling (FDM) method, one of the additive manufacturing techniques. A hybrid optimization algorithm developed in this paper was employed in the optimization process. The validation of the optimized product, developed based on analyses and optimization studies conducted using finite element software, was carried out experimentally. This study demonstrated that PA6 GF30 can be effectively utilized in the development of energy absorbers intended for use as battery protectors in electric vehicles.

2 Modified-starfish optimization algorithm (HSFOA)

For the mathematical formulation of the algorithm, two phases are proposed: the exploration and exploitation phase, followed by the algorithm's computational complexity. In the exploration phase, a five-dimensional search pattern has been added to identify a better location for the starfish. Here, for multidimensional problems and unidimensional problems, the limits are set as $D \geq 5$ and $D < 5$, respectively. This being said, the starfish has five arms, each with an eye at the end of each arm. Accordingly, the best position using the arms in all directions can be modeled as per Equation (1) [3].

$$\begin{cases} Y_{i,p}^{T} = X_{i,p}^{T} + a_1\left(X_{\text{best},p}^{T} - X_{i,p}^{T}\right)\cos\theta, & r \leq 0.5 \\ Y_{i,p}^{T} = X_{i,p}^{T} - a_1\left(X_{\text{best},p}^{T} - X_{i,p}^{T}\right)\sin\theta, & r > 0.5 \end{cases} \tag{1}$$

The parameters can be given by Equations (2) and (3).

$$a_1 = (2r - 1)\pi \tag{2}$$

$$\theta = \frac{\pi}{2}\frac{T}{T_{\max}} \tag{3}$$

The same can be given by Equation (4) [3].

$$X_{i,p}^{T+1} = \begin{cases} Y_{i,p}^{T} & l_{b,p} \le Y_{i,p}^{T} \le u_{b,p} \\ X_{i,p}^{T} & \text{otherwise} \end{cases} \quad (4)$$

Accordingly, a single arm is employed to identify the location of the food, and the position of the species has been decided. The same can be given by Equation (5) [3].

$$Y_{i,q}^{T} = E_t X_{i,p}^{T} + A_1\left(X_{k_1,p}^{T} - X_{i,p}^{T}\right) + A_2\left(X_{k_2,p}^{T} - X_{i,p}^{T}\right) \quad (5)$$

In the exploitation phase, two strategies are modeled. The first one is the preying phase, during which starfish employ the signal from nearby starfish to identify the location of the prey. Accordingly, to update the position for a better solution out of the five distances from the other starfish, two of them are selected and the position is updated. The distance and updating phenomena are modeled as per Equations (6) and (7), respectively [3].

$$d_m = \left(X_{\text{best}}^{T} - X_{m_p}^{T}\right), \quad m = 1, \ldots, 5 \quad (6)$$

$$Y_i^{T} = X_i^{T} + r_1 d_{m1} + r_2 d_{m2} \quad (7)$$

with d_m: considered five distances between the global best and current starfish position, r_1 and r_2: random numbers vary in the range of 0–1.

In the second subphase, starfish are sometimes injured by the predator, leading to damage to one of the arms during this collision. The process of regeneration of the arm again starts. However, this phase is only observed in the last starfish, leading it to move very slowly and take several months to grow. The same can be modeled as per the Equations (8) and (9) [3].

$$Y_i^{T} = \exp\left(\frac{-T \times N}{T_{\max}}()_i^{T}\right) \quad (8)$$

$$X_i^{T+1} = \begin{cases} Y_i^{T} & l_b \le Y_i^{T} \le u_b \\ l_b & Y_i^{T} < l_b \\ u_b & Y_i^{T} > u_b \end{cases} \quad (9)$$

The starfish optimizer was evaluated in comparison to the engineering component optimization findings from the CEC test suites. Nonetheless, enhanced or altered versions of the fundamental MH algorithms are always useful in the optimization study field. In this research, the SFO algorithm is combined with a dynamic oppositional-based learning technique and a piecewise chaotic map to enhance exploration and exploitation capabilities. Equation (10) provides the dynamic opposite component [13].

$$Y^{\text{DO}} = Y + r_1\left(Y^{\text{RO}} - Y\right) \quad (10)$$

3 Application of HSFOA on engineering components

The modified starfish algorithm based on dynamic oppositional-based learning and piecewise chaotic maps is used for optimizing different engineering components for performance evaluations. Moreover, the obtained statistical results are compared with those available in the literature. The tested engineering components are piston lever for weight optimization, car crash study, welded beam, and structural optimization of the truss system.

3.1 Volume optimization of the piston lever

Optimizing the various piston components and reducing capacity in terms of the volume when the piston lever is lifted are the main objectives of this optimization problem, as seen (shown) in Figure 2 [2]. The results in Table 1 demonstrate that, in contrast to other algorithms, the hybrid starfish optimization algorithm using the dynamic oppositional-based strategy and piecewise chaotic map can solve the piston lever design problem's lowest cost. In addition, the DOL (dynamic oppositional-based) allows the SF optimizer to find the piston lever design's second-smallest cost. Overall, the DOL and piecewise chaotic map combined with the SFOA realized the optimized solution with

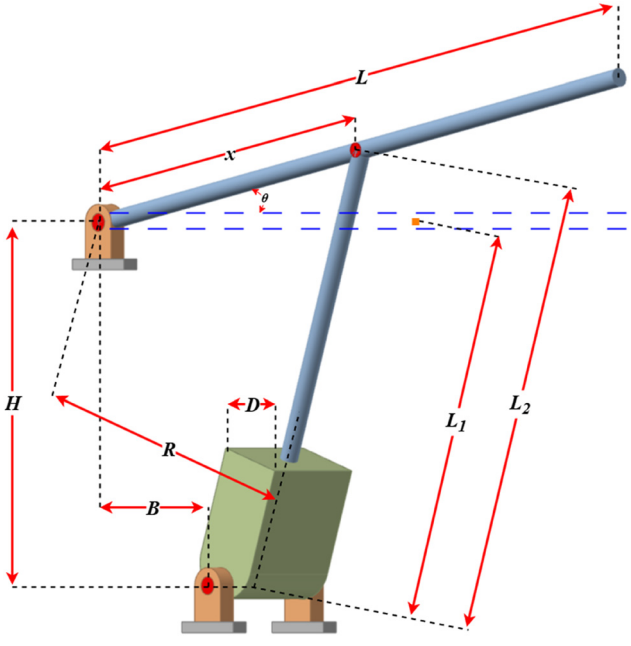


Figure 2: Piston lever design with design parameters to be optimized.

Table 1: Statistical results comparison from the literature with modified starfish optimizer.

Algorithms	Optimization results
HSFOA	8.412
CSFOA	8.413
Hunger games search optimizer	8.418
Artificial rabbits algorithm	8.422
Ship rescue optimizer	8.425
Prairie dog optimizer	8.428

Table 2: Statistical results comparison from the literature with the improved starfish optimizer.

Algorithm	Optimal cost
HSFOA	22.8429
CSFOA	22.8430
Hunger games search optimizer	22.8532
Artificial rabbits algorithm	22.9536
Ship rescue optimizer	22.9852
Prairie dog optimizer	23.1523

improved convergence and robustness, reducing the overall cost of the studied component and improving the method's optimization efficacy.

3.2 Car side crash design

A car body, as shown in Figure 3, is subjected to different crashing tests over the eight targeted points of the frame. Moreover, the overall motivation is to reduce the weight of the car frame by safeguarding the car frame. There are 10 design variables in the optimization problem [43].

The results in Table 2 show that, in comparison to the examined methods in the car side impact design problem, the optimal cost of the HSFOA algorithm has been much decreased. The HSFOA method can find the lightest automobile weight out of all the algorithms. In addressing the automobile side impact design, the simulation results show that the starfish algorithm with a dynamic oppositional-based learning technique and chaotic map showcases effectiveness in attaining a global optimum solution with higher optimization accuracy and stronger stability.

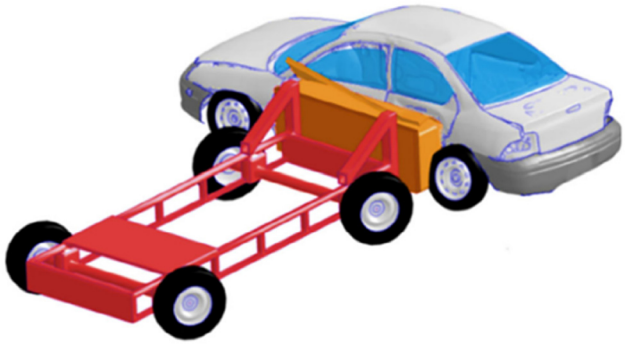


Figure 3: Car crash side impact.

3.3 Structural optimization of 3-bar truss design problem

The goal of the problem is to reduce a metallic structure's weight while taking stress limitations into account. The cross-sectional areas of the three structural components serve as the decision factors [2]. Figure 4 and Table 3 show a problem layout and a comparison of the solutions produced by cutting-edge algorithms.

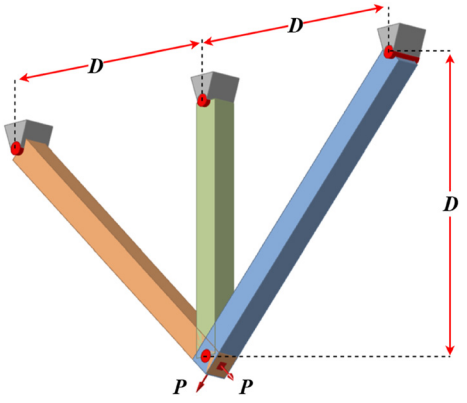


Figure 4: 3-Bar truss for structural optimization.

Table 3: Statistical results comparison from the literature with hybrid starfish optimizer.

Algorithm	$f(x)$
HSFOA	263.89584
CSFOA	263.89632
Hunger games search optimizer	263.98563
Geyser inspired algorithm	263.99102
Ship rescue optimizer	264.01123
Prairie dog optimizer	264.14032
Electric eel foraging optimizer	264.25362

3.4 Energy absorber design for the electric vehicle battery pack

One of the most important components of electric vehicles (EV) is the electric vehicle battery enclosure. The location of the energy absorber in the electric vehicle battery case system is displayed in Figure 5.

In the study of the optimum design of energy absorbers used in the battery pack of EV, the method developed within the scope of the project was applied. Energy absorbers are structural elements that convert the kinetic energy generated during a collision into deformation energy, as shown in Figure 5.

In the numerical studies, the energy absorbers were fixed at one end, and the force was applied in compression in the axial direction with a rigid wall at the other end. The fixed energy absorbers were forced to compress in the axial direction. The rigid walls defined are planar and non-deformable. Figure 6 shows the boundary conditions applied to the initial model energy absorber and the rigid wall.

The deformation occurring at the boundary conditions is given in Figure 7.

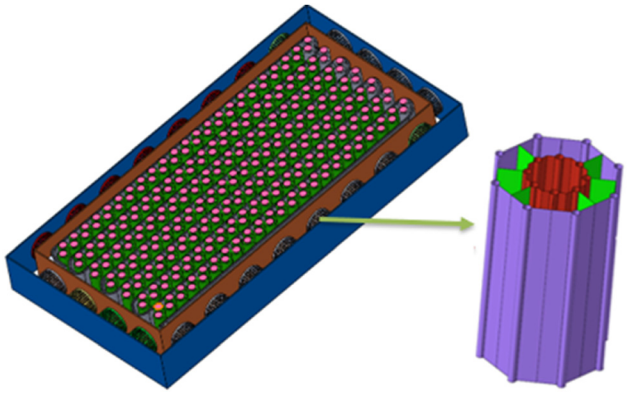


Figure 5: Electric vehicle battery pack and crash box.

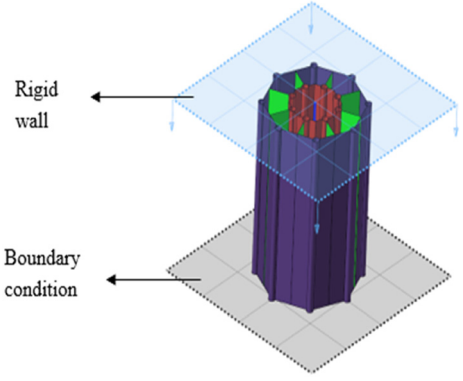


Figure 6: Boundary conditions.

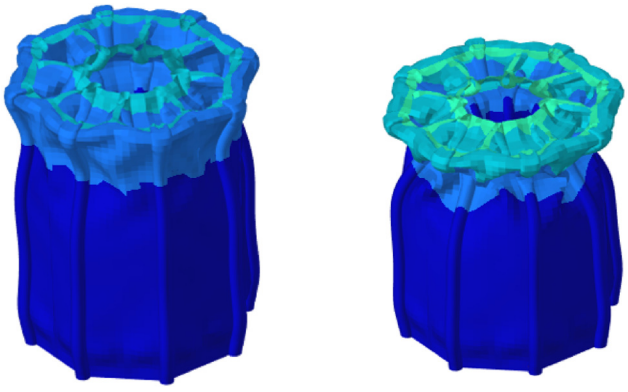


Figure 7: First design of multicell energy absorber with deformed shape after crash.

The HSFOA algorithm is used in this study to optimize the design of the crash box. Accordingly, the variable ranges in the predefined limits of 1–4, 1–4, 0.6–2, and 0.6–2, respectively.

The energy absorber with the boundary conditions in Figure 6 was optimized with the design variables in Figure 8 to maximize the minimum weight and specific energy absorption and minimize the peak forces. The final optimum design and deformation after a crash are shown in Figure 9.

In this study, the dynamic fracture behavior of energy absorbers produced using additive manufacturing was investigated through drop weight tests performed at room temperature. The experimental setup included a total impact mass of 580 kg and an impact velocity of 2,700 mm/s.

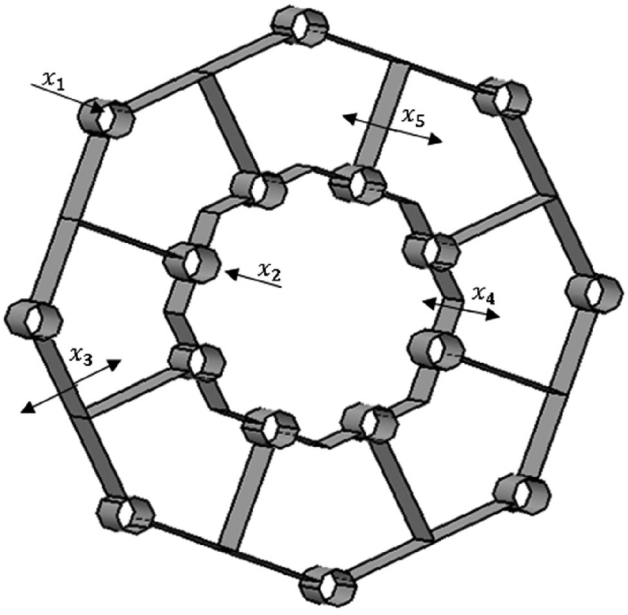


Figure 8: Design variables for optimization.

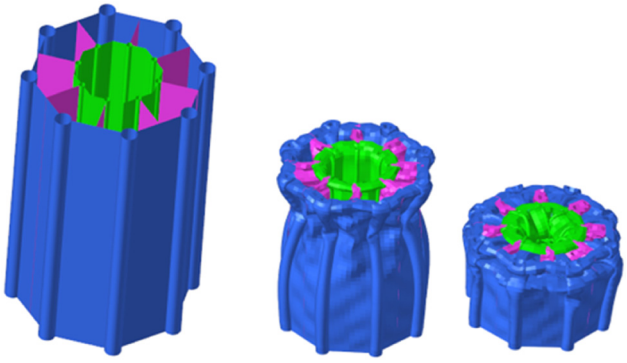


Figure 9: Final design.



Figure 10: Experimental result of the final design.

Table 4: Proposed design of the energy absorber by the hybrid starfish optimizer.

Optimizer	Energy absorption (kJ)	Maximum force (kN)	Mass (g)
Initial design	4.6	40.1839	68.39
Geyser inspired algorithm	4.9	39.6	62.2
Starfish algorithm	5.2	38.6	61.5
HSFOA	5.6	35.3	59.3
Experimental results	5.7	35.4	59.3

Each test was repeated five times, and the average values were reported. During testing, the impact force and displacement were measured using load and displacement sensors. Figure 10 shows experimental results for the optimal design.

Table 4 compares the optimization studies performed by different methods. As shown in Table 4, HSFOA improves the crash performance of the battery case of electric vehicles, reducing the mass of the energy absorber.

4 Conclusions

In this study, a multicell energy absorber is designed and developed to enhance the protection of electric vehicle battery enclosures against impact and collision scenarios. During the design phase, a new starfish optimization algorithm (HSFOA) combining the starfish optimization algorithm, dynamic oppositional-based learning, and a piecewise chaotic map is proposed to determine the most effective geometry in terms of energy absorption capacity. The mechanical behavior of the optimized structures was extensively investigated through finite element analysis (FEA). Additionally, artificial intelligence-based prediction and optimization models were developed using the data obtained from the simulations, significantly reducing computation time and cost.

The energy absorbers were fabricated using PA6 GF30. The printed samples were experimentally evaluated via drop weight impact tests conducted at room temperature, and the results were compared with the numerical predictions. The findings demonstrated a high level of agreement between the experimental results and the simulation data supported by AI models.

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Informed consent: Not applicable.
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Conflict of interest: The author states no conflict of interest.
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