Bu-Ali Sina University

Biosystems Engineering & Sustainable Technologies (BEST)

Journal Homepage: www.best.basu.ac.ir/
BEST J., 2(1) (2025) 21-29
DOI: https://doi.org/10.22084/best.2025.31229.1009

Comparative Study between the Gravitational Search Algorithm and Fire Hawk Algorithm in an Off-Road Seat Suspension Optimization

Mohammad Gohari [1]*, Mona Tahmasebi [2], Mohammad Mobarakabadi [1]

[1] *Faculty of Mechanical Engineering, Arak University of Technology, Arak, Iran.*

[2] *Department of Agricultural Engineering, Markazi Agricultural and Natural Resources Research and Education Center, Agricultural Research, Education and Extension, Organization (AREEO), Arak, Iran.*

PAPER INFO

Paper history:
Received: Jul. 09, 2025
Revised: Oct. 12, 2025
Accepted: Nov. 15, 2025
Available Online: Dec. 30, 2025

Keywords:
Seat Suspension
Optimization
Meta-Heuristic Techniques
Gravitational Search
Fire Hawk Optimization Algorithm

ABSTRACT

Long-term driving of Off-Road Vehicles increases the risk of damage to some organs of humans, such as the spinal column or digestive system. Whereas seat suspensions are used in heavy-duty off-road vehicles, adjusting the parameters of them is crucial. Recently, non-gradient optimization methods have been focused on by researchers to tune these parameters, such as spring constant, damper coefficient, and seat pan mass. Current work represents the application of two Meta-Heuristic techniques (Gravitational Search (GSA)and Fire Hawk Optimization Algorithms (FHOA)) to minimize transmitted vibration from the cabin floor to the seat pan. According to the GSA, the amplitude of seat displacement is around 2×10^{-5} (m). Moreover, the first peak is reached at 0.95×10^{-5} at 8Hz. In addition, according to the FHOA, the magnitude of output via FHOA optimum parameters is 0.8×10^{-5}, in the time domain. On the other hand, in the frequency domain, the first peak is gotten 4.2×10^{-6}. So, it shows that the performance of passive seat suspension, which is adjusted with GSA, is more enhanced in comparison to FHOA. In conclusion, the outcomes of optimization via simulation show that GSA has a better performance compared to FHOA, and the seat suspension tuned by that can diminish the vibration with notable diminishment.

1. Introduction

The human body can be harmed from transmitted vibration from external sources such as vehicles, excavation devices, pneumatic pick hammers, etc. This unwanted vibration can damage to spine column, eye, heart, and digestive system based on the dominant frequency of vibration (Wikström et al., 1994). With the industrialization of human life and the wide range of vehicles used in daily life, the risk of these harmful problems has increased drastically (Linan et al., 2008, Yanxi & Qingxia, 2010). When a human is exposed to unwanted vibration in the short term, the heart rate may be increased, or muscle tension can be created. In the long term, serious problems can be accrued, such as abnormality in spine vertebrates or malfunction in the urinary and digestive system (Paddan & Gri, 2002, Bainbridge et al., 2025 & Qiao et al., 2025). Heavy-duty off-road vehicles such as loaders, graders, bulldozers, and agricultural tractors employ seat suspension to isolate the driver's body from unwanted vibration because most of them do not use primary suspension. Moreover, most heavy-duty off-road vehicle seat suspensions are passive because to cost of active seat suspensions is high. Thus, parameter design of suspension is very crucial, and many researchers are focused on that to find the optimum coefficients. Commonly, a passive seat suspension consists of a spring, damper, and seat pan mass (Barton & Fieldhouse, 2024). Previously, some researchers have utilized mathematical optimization methods for this purpose (Yan et al., 2015, Maniowski, 2014 & Pazooki et al., 2012).

The performance and accuracy of optimization are a crucial aspect of engineering, science, and decision-making, where the goal is to find the best possible solution under given constraints. Traditional mathematical optimization methods, such as gradient-based techniques, linear programming, and Newton-based approaches, are effective but often struggle with complex, non-linear, multi-modal, and high-dimensional problems. In contrast, evolutionary algorithms (EAs), inspired by natural selection and biological evolution, have emerged as powerful alternatives for solving such complex optimization problems. Common evolutionary algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), etc. The GA mimics the process of natural selection, using operators like selection, crossover, and mutation to evolve solutions over multiple

*Corresponding author's email: moh-gohari@arakut.ac.ir

Please cite this article as: Gohari, M., Tahmasebi, M., & Mobarakabadi, M., (2025). Comparative Study between the Gravitational Search Algorithm and Fire Hawk Algorithm in an Off-Road Seat Suspension Optimization. *Biosystems Engineering & Sustainable Technologies (BEST)*, *2*(1), 21-29. https://doi.org/10.22084/best.2025.31229.1009

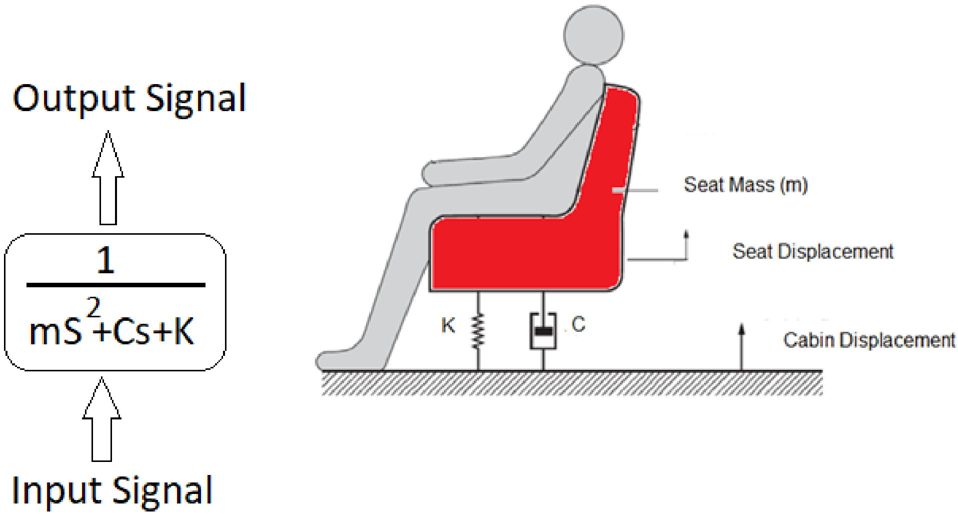

Fig. 1. The seat suspension parameters and corresponding transfer function.

generations. The PSO is inspired by the social behavior of birds and fish, where particles (potential solutions) adjust their positions based on their own best experience and the swarm's collective intelligence. ACO is based on the foraging behavior of ants, using pheromone trails to find the optimal paths in a problem space. Unlike gradient-based methods, which may get trapped in local optima, EAs perform global searches, making them more suitable for non-convex and multi-modal problems. Moreover, Mathematical optimization often requires derivatives of the objective function, which may not be available or computationally feasible. EAs do not require gradient information, making them highly flexible. Furthermore, Evolutionary algorithms can efficiently explore large search spaces and handle problems with many variables. Also, EAs, such as NSGA-II (Non-dominated Sorting Genetic Algorithm), are well-suited for multi-objective optimization, where multiple conflicting objectives must be optimized simultaneously.

Based on EAs aspects, novel evolutionary optimization techniques have been utilized recently by designers for seat suspension optimization, such as genetic algorithm, particle swarm algorithm or artificial neural network (Abbas et al., 2013, Gadhvi et al., 2016, Gad et al., 2017, Gohari & Tahmasebi, 2022, & Gohari et al., 2011). Three Meta-Heuristic methods of optimization (GA, PSO, and HS) were tested in passive seat suspension, and results show that the Harmonic Search Algorithm reached better parameters based on verification by computerized evaluation (Gohari & Tahmasebi, 2014), although the optimized values were close to particle swarm optimization (PSO) (Gohari et al., 2013). In addition, these evolutionary methods are applied to active seat suspensions (Zhang et al., 2024, Gad et al., 2025, & Zhao et al., 2024).

The current study aims to find feasible parameters of seat suspension via new EAs techniques, including Fire Hawk (FHOA), and Gravitational Search Algorithm (GSA), and verify the results by a simulation study. The main aim of this work is to study the performance of GSA and FHOA in finding global optimum values and checking the feasibility of the found values. Comparison study of the result of this study to the other method unveils the cores and pones of these methods.

2. Materials and Methods

To optimize the seat suspension via GSA and FHOA, firstly, a transfer function is considered for this structure, which is shown in Fig.1. In fact, the vibration transmissibility is taken as the objective function. Three parameters are unknown and must be identified based on the optimization method: seat pan mass(m), spring constant (K), and damper coefficient (C). Three constraints are set in these ranges because they are commercially available in the market:

$$10 \ll C \ll 100\left(\frac{Ns}{m}\right)$$

$$1000 \ll K \ll 10000\left(\frac{N}{m}\right)$$

$$1 \ll m \ll 20(Kg)$$

The output of the transfer function is reached when a sinusoidal signal is applied to the system, and the response of that is calculated. The frequency of the excitation (input) signal is 8 Hz, and the amplitude that 10e-3(m).

2.1. GSA Optimization

The **Gravitational Search Algorithm (GSA)** is a nature-inspired optimization method introduced by Rashedi, Nezamabadi-Pour, and Saryazdi in 2009. It is based on **Newton's law of gravity and motion**, where candidate solutions (agents) interact through gravitational forces. GSA is classified as a **metaheuristic optimization algorithm** and is widely used in solving complex optimization problems, including engineering design, machine learning, scheduling, and control systems. GSA simulates the movement of objects under the influence of gravity. Each solution in the search space is considered as an **agent (mass)** that attracts other agents based on their fitness value (similar to gravitational force). The fundamental steps in GSA are as follows:

1. Agent Representation
- Each agent (candidate solution) is considered as an object with a certain mass.
- Agents with **better fitness values** have **higher masses**, meaning they exert a stronger gravitational force on others.

2. Fitness-Based Attraction
- Heavier agents (better solutions) attract lighter agents, guiding them towards potentially optimal solutions.
- Over time, solutions converge towards the best possible solution through collective movement.

3. Updating Position and Velocity
- The acceleration of each agent is computed based on the total gravitational force acting on it.
- Agents update their positions dynamically, simulating the natural attraction of objects under gravity.

2.1.1. Mathematical Formulation of GSA

Gravitational Constant (G), The strength of attraction decreases over time:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \tag{1}$$

Where G_0 is the initial gravitational constant, α is a decay factor, t is the current iteration, and T is the total iterations. The mass of each agent is determined based on its fitness:

$$M_i = \frac{f_i - f_{worst}}{f_{best} - f_{worst}} \tag{2}$$

Where f_i is the fitness of the agent, and f_{best} and f_{worst} represent the best and worst fitness values in the population.

The force exerted by an agent **j** on agent **i** is given by:

$$F_{ij} = G \frac{M_i M_j}{R_{ij} + \varepsilon} \left(X_j - X_i \right) \tag{3}$$

The acceleration of agent **i** is calculated as:

$$a_i = \frac{F_i}{M_i} \tag{4}$$

Where R_{ij} is the Euclidean distance between agents, and ε is a small constant to prevent division by zero.

The velocity of each agent is updated as follows:

$$V_i(t+1) = rV_i(t) + a_i(t) \tag{5}$$

Also, the position is updated based on velocity:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{6}$$

Where r is a random number in the range [0,1] to introduce stochastic behavior. GSA dynamically adjusts the attraction forces, allowing efficient exploration in early stages and convergence in later stages. Unlike gradient-based methods, GSA can handle non-differentiable, complex, and multi-modal functions.

2.2. Fire Hawk Optimization Algorithm

The **Fire Hawk Optimization Algorithm (FHOA)** is a nature-inspired metaheuristic algorithm that mimics the hunting strategy and survival behavior of fire hawks, a species of raptors found primarily in Australia. Fire hawks are known for their unique and intelligent behavior of spreading fire intentionally to flush out prey from their hiding spots. This remarkable strategy of using controlled fires to optimize hunting efficiency inspired the development of the FHOA, which is designed to solve complex optimization problems in various fields, including engineering, machine learning, and control systems.

In nature, fire hawks exhibit two key behaviors:

1. Fire Spreading: Fire hawks pick up burning sticks and drop them in dry areas to start controlled fires. This forces prey (small animals, insects, etc.) to flee from their shelters, making them easier to catch.

2. Hunting Strategy: Fire hawks actively search for prey in both burned and unburned areas, adapting their strategy based on environmental conditions.

The **Fire Hawk Optimization Algorithm** translates these natural behaviors into mathematical models for solving optimization problems. The process of spreading fire and adapting to dynamic environments provides a balance between **exploration** (searching new areas) and **exploitation** (refining existing solutions).

The key components of the FHOA are population initialization, fire spreading mechanism, hunting and prey capture(Exploitation), and adaptation strategy.

2.2.1. Mathematical Formulation of FHOA

a. Initialization:

Firstly, the definition of the population size (N), the maximum number of iterations (T), and problem boundaries must be considered.

Then, the random initialization of the positions of fire hawks (X_i) within the search space must be done. In this optimization, the initial population of hawks is 30, and 100 iterations are executed.

b. Fitness Evaluation:

Each fire hawk's position represents a candidate solution, and the evaluation of the **fitness function** will be applied to determine the quality of each solution.

c. Fire Spreading (Exploration):

Normally, generating new candidate solutions is executed by perturbing current positions:

$$X_{new} = X_i + \propto \left(rand\,(n) - 0.5\right)\left(X_{best} - X_i\right) \tag{7}$$

Where α is a control parameter, rand(n) is a random number between 0 and 1, and X_{best} the current best solution.

d. Hunting Strategy (Exploitation):

The fire hawk position is adjusted to move closer to the best-known solution:

$$X_i^{(t+1)} = X_i^t + \beta\left(X_{best} - X_i\right) \tag{8}$$

Where β is an exploitation factor that decreases over time, focusing on fine-tuning solutions.

e. Adaptation Mechanism:

Dynamic adjustment of exploration and exploitation parameters is done as the algorithm progresses to ensure convergence to the optimal solution.

f. Termination Criteria:

The algorithm terminates when the maximum number of iterations is reached or when the improvement between successive iterations falls below a threshold. Generally, the exploration capability of the FHOA is higher than PSO or GA, while the convergence speed is fast with low complexity.

3. Results and Discussion

The primary objective of this study was to minimize vibration transmission from a vehicle seat to the human body by optimizing the seat's mass, spring constant, and damper coefficient. The optimization was successfully performed using two distinct metaheuristic algorithms: the Fire Hawk Optimization Algorithm (FHOA) and the Gravitational Search Algorithm (GSA). The results presented in Table 1 reveal that while both algorithms converged on viable solutions, they identified distinctly different parameter sets. This section interprets these findings, evaluates the algorithms' performance, and considers the practical implications of the optimized designs.

The optimum points of the cost function are reached by two techniques: the Gravitational Search Algorithm and the Fire Hawk Optimization Algorithm. As mentioned before, three parameters are formulated in the problem definition to minimize transmitted vibration from vehicle to human body: Mass, spring constant, and damper coefficient. Table 1 shows the reached parameters by the GSA and FHOA algorithms.

The parameter sets obtained by FHOA and GSA suggest two different philosophical approaches to vibration isolation. The FHOA solution proposes a markedly lighter seat pan (1.15 kg vs. 2.66 kg) with a significantly softer spring constant (2868 N/m vs. 6754 N/m) and a lower damping coefficient (10 Ns/m vs. 22.22 Ns/m). This configuration likely aims to create a highly isolated system where the seat's natural frequency is tuned well below the dominant input frequency (8 Hz), leveraging the isolation region of the transmissibility curve. The low damping preserves this isolation effect, as excessive damping can degrade isolation performance at higher frequencies.

Conversely, the GSA solution proposes a heavier, stiffer, and more heavily damped system. This design may prioritize limiting the maximum displacement (rattle space) of the seat, a critical practical constraint in vehicle design. The higher damping is particularly effective at suppressing resonance amplitudes, which might be a strategic choice if the input

Table 1. The optimum parameters which are obtained by two algorithms

Parameter	FHOA	GSA
Seat Pan Mass (KG)	1.1477	2.6551
Damper Coefficient (NS/M)	10	22.2173
Spring Constant (N/M)	2868.0921	6754.2518

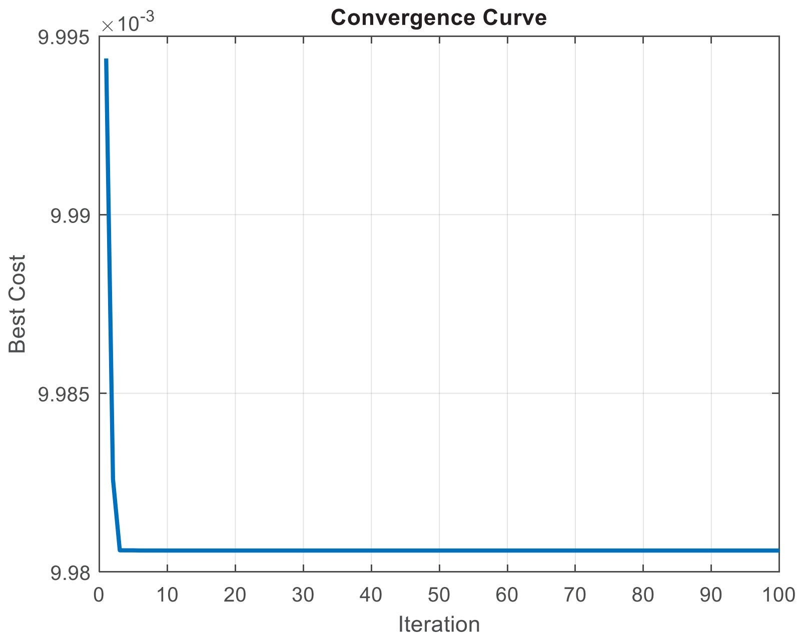

Fig. 2. The convergence curve of optimization by FHOA

vibration spectrum is broad or if there is a risk of the system passing through resonance during transient events. The significant discrepancy in solutions highlights a classic trade-off in suspension design: the conflict between achieving excellent isolation (favored by soft springs and low damping) and controlling static deflection and resonant amplification (favored by stiffer springs and higher damping).

3.1. Algorithm Performance and Convergence

The convergence behavior, as illustrated in Fig. 2, is crucial for evaluating the efficacy of the FHOA. A rapid initial convergence followed by a stable plateau suggests that the FHOA is an efficient and robust optimizer for this engineering problem. It demonstrates a strong ability to escape local minima and navigate the complex, likely non-linear and high-dimensional, search space of the suspension design problem. While a direct comparison of convergence speed with GSA is not provided, the fact that both algorithms found valid yet different optima underscores a key characteristic of metaheuristics: their solution can be influenced by their unique exploitation/exploration mechanisms. The FHOA, inspired by the fire-seeking behavior of birds, may have a different exploratory profile compared to the mass-interaction principles of GSA, leading it to a different region of the solution space.

The convergence curve of optimization by FHOA is unveiled in Fig. 2. Also, the response of seat suspension to a sinusoidal signal in the time domain is demonstrated in Fig.3. The amplitude of that is around 2×10^{-5} (m). Moreover, the first peak is reached at 0.95×10^{-5} at 8Hz (Fig.4)

Fig.5 shows GSA finds the optimum parameters after 35 iterations, while FHOA executed that faster. The magnitude of output via FHOA optimum parameters is 0.8×10^{-5}, in the time domain. On the other hand, in the frequency domain, the first peak is obtained at 4.2×10^{-6}. So, it shows that the performance of passive seat suspension, which is adjusted with GSA, is more enhanced in comparison to FHOA.

In fact, the peak of the seat pan in the frequency domain identified by FHOA is 20 times greater than GSA. Thus, in practical modification, the seat suspension parameters must be adjusted and modified based on values that are optimized by GSA.

3.2.Vibration Isolation Performance

The performance of the optimized system, particularly the FHOA design, is exceptionally promising. A maximum amplitude of approximately 20 µm (Fig. 3) in response to a sinusoidal input is a remarkably low value, indicating superb vibration attenuation. The frequency response (Fig. 4) confirms this, with a first peak transmissibility of only 0.95×10^{-5} at 8 Hz. This low transmissibility peak is the core achievement of the optimization, as it directly correlates to reduced vibration exposure for the occupant, which is linked to improved comfort, reduced fatigue, and lower health risks associated with long-term whole-body vibration.

3.3. Implications and Practical Considerations

From a practical standpoint, the FHOA solution appears highly attractive due to its lower mass, which aligns with the automotive industry's relentless pursuit of weight reduction for improved fuel efficiency. However, the very soft spring

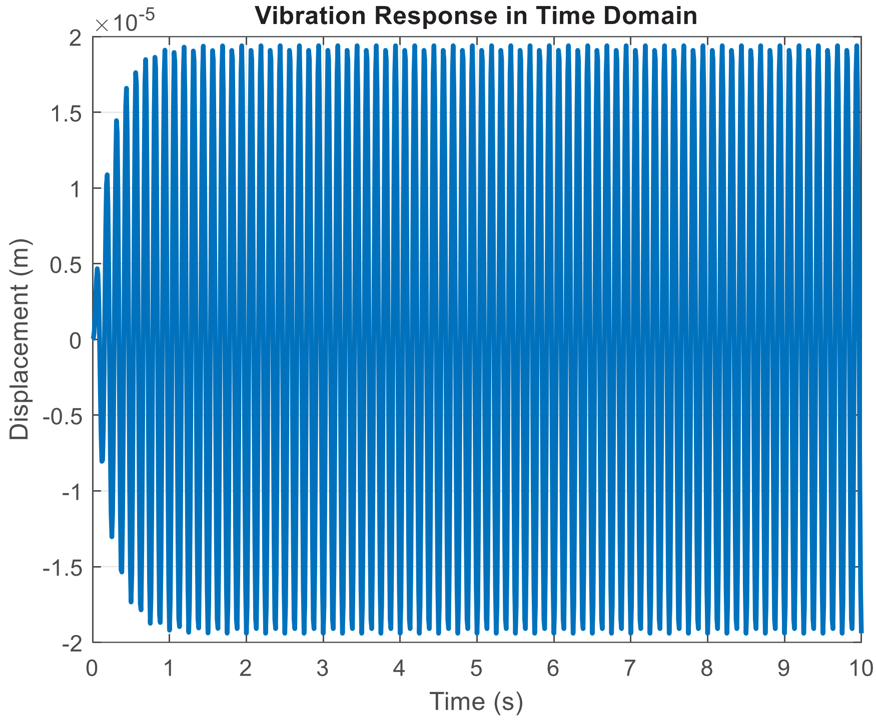

Fig. 3. The response of the seat suspension when exposed to a sinusoidal signal in the time domain.

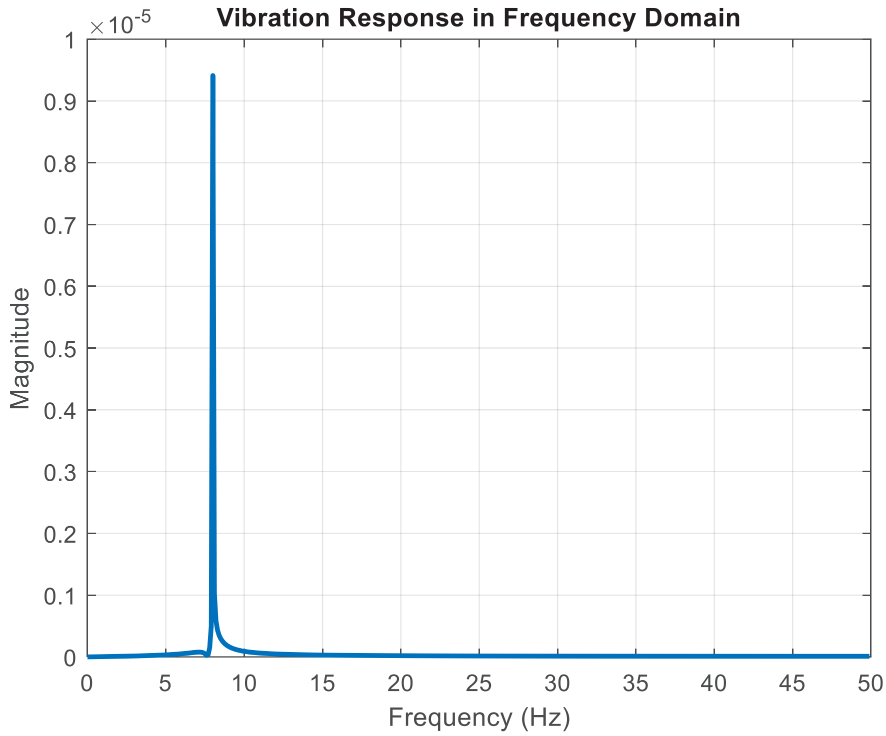

Fig. 4. The peak of seat pan displacement in the frequency domain.

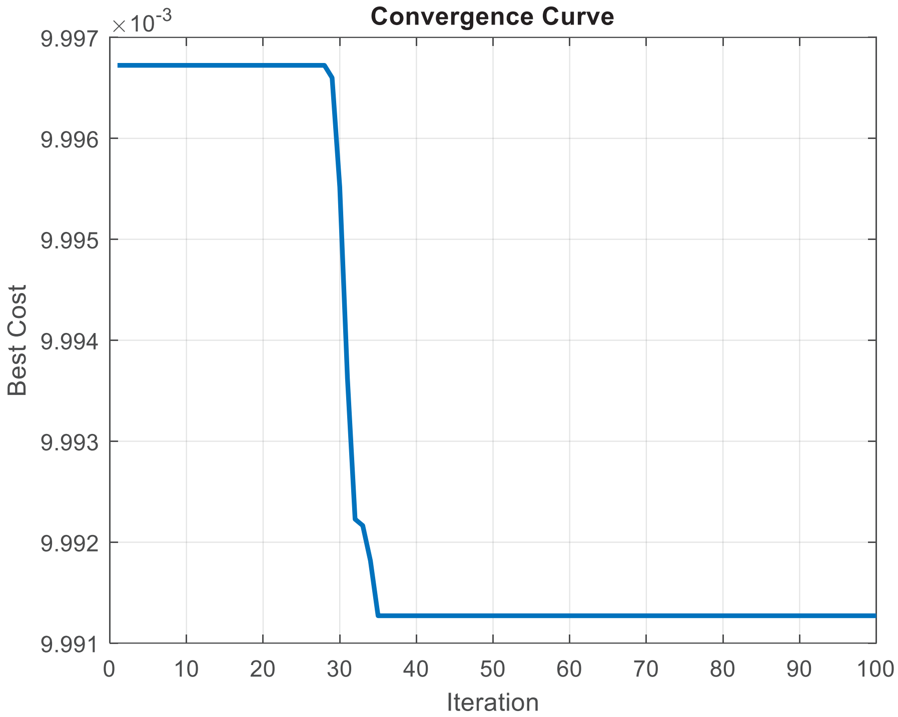

Fig. 5. The convergence curve of optimization by GSA.

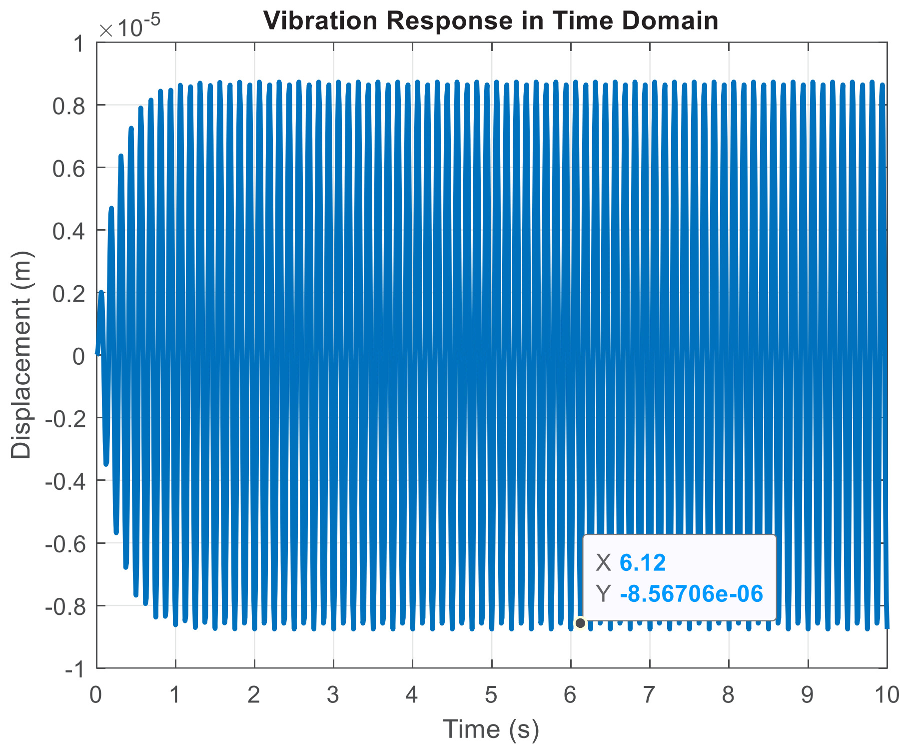

Fig. 6. The displacement of the seat pan by a sinusoidal signal applied to the seat suspension, in the time domain

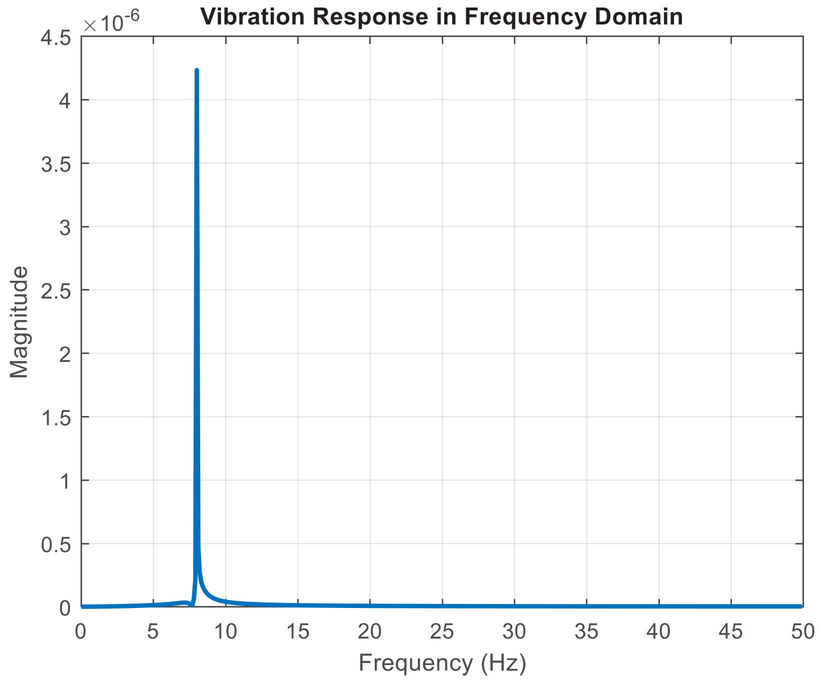

Fig. 7. The peak of seat pan displacement reached by the GSA method, in the frequency domain

and low damping raise important questions about the system's performance beyond the tested sinusoidal condition. Its behavior under large-amplitude transient inputs (e.g., driving over a pothole) or its susceptibility to bottoming out must be rigorously evaluated. The GSA solution, while heavier, offers a more conservative and potentially more robust design with its higher stiffness and damping.

3.4. Limitations and Future Work

This study has several limitations that point to valuable future research directions. The optimization relied on a single sinusoidal input and should be extended using standardized road profiles like ISO 8608 for real-world relevance. Furthermore, replacing the simplified human body model with an advanced biodynamic model and employing multi-objective optimization would better capture the trade-offs between vibration isolation, seat travel, and mass[21].

4. Conclusion

As mentioned previously, seat suspension plays a crucial role in shock and vibration absorption generated by road terrain for drivers of heavy-duty off-road vehicles. The identification of optimum parameters for seat suspension is necessary and has recently been applied by Metaheuristic approaches. Current work shows that minimum vibration may be transmitted to the driver's body with optimized values via GSA, although FHOA executed optimization of the cost function faster with a lower number of iterations. In fact, GSA reduced seat pan vibration amplitude by 80% compared to FHOA.

In conclusion, both the Fire Hawk Optimization Algorithm and the Gravitational Search Algorithm proved effective in solving the complex problem of vehicle seat vibration isolation, albeit arriving at different design optima. The FHOA-produced design, characterized by low mass, stiffness, and damping, demonstrates exceptional theoretical performance for the given sinusoidal input and presents a compelling lightweight solution. The choice between the two designs ultimately depends on broader vehicle design constraints and the need for performance robustness across a wider range of operating conditions. This study successfully demonstrates the potent application of advanced metaheuristics in tackling fundamental engineering challenges in automotive comfort and design. In future work, these obtained values will be studied by an experimental test with real road unevenness.

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