

HYBRID METAHEURISTIC OPTIMIZATION AND EXPERIMENTAL VALIDATION OF AN 8-DOF OCCUPANT-WHEELCHAIR VIBRATION MODEL USING GA, PSO, DE AND HYBRID APPROACHES

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ABSTRACT. *This paper develops and validates an eight-degree-of-freedom (8-DOF) occupant-wheelchair vibration model that captures the coupled mechanical and biomechanical responses of seated occupants under vertical excitation from 0 to 20 [Hz]. Four meta-heuristic optimization algorithms – Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and a sequential Hybrid GA-PSO-DE – are employed to identify mass, damping, and stiffness parameters within biomechanical constraints. Three commercial seat-cushion configurations are examined, including Jay J2 Deep Contour representing gel-based behavior, ROHO High Profile representing air-based performance, and Comfort Mate Foam representing foam-based viscoelasticity. The Hybrid GA-PSO-DE method achieved the lowest normalized cost ($J_{avg} \approx 0.11$), minimum transmissibility error ($RMSE_{|\Delta T|} \approx 0.045$), and the highest experimental agreement of 94-96[%]. All optimized models accurately reproduced the primary torso-spine resonance within 3-4 [Hz] and maintained phase coherence within ± 3 [°]. Material-dependent analysis revealed that gel cushions provided maximum isolation, air cushions balanced comfort and damping, and foam cushions offered high stiffness and postural stability. The validated Hybrid GA-PSO-DE framework delivers high predictive fidelity, computational efficiency, and biomechanical realism, forming a robust foundation for seat-cushion optimization and vibration-based comfort assessment consistent with ISO 2631-1 standards.*

Keywords: Occupant-wheelchair dynamics, Vibration transmissibility, Biomechanical modeling, Optimization algorithms, Hybrid GA-PSO-DE optimization

1. Introduction. Wheelchair vibration is not only a matter of mechanical performance but also a decisive factor influencing human health, comfort, and long-term musculoskeletal integrity [1, 2]. Every irregularity on the ground transmits dynamic energy through the tires, frame, and seat, ultimately reaching the occupant's spine and soft tissues [3, 4]. For individuals who rely on wheelchairs as their primary means of mobility, prolonged exposure to whole-body vibration (WBV) can lead to discomfort, fatigue, and increased risk of low back pain and spinal degeneration [5, 6]. Understanding and mitigating vibration transmissibility within the occupant-wheelchair system is therefore essential for

both engineering design and clinical safety [7, 8, 9]. The key challenge lies in accurately modeling how vibration propagates through the coupled human-wheelchair structure and in quantifying the influence of seat-cushion properties on dynamic transmission [10, 11].

Despite progress in vehicle and seating dynamics, wheelchair vibration modeling remains comparatively underdeveloped [12, 13, 14]. Most prior analyses depend on empirical testing or low-order lumped-mass representations that capture only the gross motion of the seat or chassis [15, 16]. Typical one- and two-degree-of-freedom (DOF) systems can estimate resonance frequencies but cannot represent distributed stiffness and damping effects across anatomical segments [17, 18]. Consequently, transmissibility predictions often diverge across different cushion constructions, particularly between air-cell, gel, and foam types that exhibit distinct viscoelastic behaviors [9, 19]. To address this, an advanced model must integrate anatomical realism, mechanical coupling, and experimental calibration [3, 20, 21].

The critical paper gap occurs at the intersection of biomechanical modeling fidelity and robust parameter optimization [22]. Earlier studies employed single metaheuristic algorithms such as Genetic Algorithm [23], Particle Swarm Optimization [24], and Differential Evolution [25] for system identification using measured transmissibility data. While each improved curve-fitting accuracy compared with manual tuning, notable algorithmic limitations persisted. GA achieved broad global exploration but converged slowly [23]. PSO provided faster search yet often stagnated around local minima [24]. DE introduced differential mutation for population diversity but required sensitive scaling to preserve numerical stability across cushions with different viscoelastic characteristics [25]. To date, no comprehensive investigation has systematically compared GA, PSO, and DE within a unified biomechanical model or validated them against multi-cushion experimental datasets [3, 19]. This absence limits the reliability of simulation frameworks that could otherwise support evidence-based design, rehabilitation planning, and cushion personalization [2, 14].

The present paper addresses these limitations by developing an anatomically inspired eight-degree-of-freedom (8-DOF) occupant-wheelchair vibration model that captures both structural and physiological vibration paths [16, 20]. The formulation includes vertical motion of the major body segments – head, torso, pelvis, and lower limbs – coupled with the compliance of the seat cushion and wheelchair frame [7, 14]. Parameter identification is performed using four metaheuristic optimizers under identical conditions: GA, PSO, DE, and a newly designed Hybrid GA-PSO-DE algorithm that integrates global search, adaptive swarm learning, and differential recombination with a local refinement stage [23, 24, 25]. This hybrid strategy enhances convergence reliability, ensures physical plausibility of parameters, and minimizes transmissibility error [21, 22]. Experimental validation uses seven commercial seat cushions – Jay J2 Deep Contour, Meridian Wave, ROHO High Profile, Vector with Vicair, ROHO Low Profile, Zoombang with Foam, and Comfort Mate Foam – spanning a wide range of structural stiffness and damping characteristics [5, 8, 9]. Measured transmissibility and phase responses within 0-20 [Hz] serve as the benchmark for model comparison [19, 20].

This paper advances the state of the art in three principal ways [13, 16]. First, it establishes a validated 8-DOF biomechanical model that bridges simplified analytical structures and experimentally observed occupant-seat dynamics [3, 14]. Second, it proposes a hybrid metaheuristic framework combining GA, PSO, and DE to achieve an optimal balance between exploration and exploitation for identifying damping and stiffness parameters [23, 24, 25]. Third, it provides a comprehensive comparative analysis linking optimized parameters to physical cushion behavior, illustrating how viscoelastic design governs transmissibility, phase response, and comfort [7, 9].

The motivation for this paper extends beyond algorithmic performance [22]. It is grounded in the belief that assistive mobility engineering should reflect human physiology so that each model parameter represents a genuine biomechanical mechanism and each optimization result translates into measurable improvements in comfort and safety [1, 2, 3]. Through integration of experimental evidence with mathematical modeling, this work transforms vibration analysis into a predictive and interpretable framework applicable to rehabilitation engineering and assistive technology design [19, 20]. The resulting model provides clinicians and researchers with a validated computational tool for evaluating vibration exposure and improving the long-term health of wheelchair users [5, 6, 8].

The broader significance of this paper lies in the convergence of engineering precision, computational intelligence, and human-centered design [16, 21, 22]. By integrating hybrid optimization with an anatomically realistic 8-DOF model, this study establishes a new benchmark for predictive accuracy in vibration transmissibility [3, 7]. The findings support data-driven cushion design, personalized comfort evaluation, and safer wheelchair configurations aligned with ISO 2631-1 comfort and health standards [1, 2, 26]. Ultimately, the paper demonstrates that experimentally validated, biomechanically grounded modeling can redefine assistive mobility design toward adaptive, evidence-based, and health-optimized wheelchair systems [8, 9, 19].

The structure of this paper is organized as follows. Section 2 formulates the coupled occupant-wheelchair dynamics using a free-body representation, defining the mechanical subsystems, anatomical coupling, and derivation of matrix equations of motion. Section 3 details the metaheuristic parameter identification process employing four optimization algorithms – GA, PSO, DE, and the staged Hybrid GA-PSO-DE – executed under identical cost functions and physical constraints to ensure fairness and reproducibility. Section 4 presents comparative results and discussion, emphasizing cross-cushion transmissibility characteristics, biomechanical interpretation of stiffness-damping behavior, and validation against experimental measurements for seven commercial wheelchair seat cushions. Finally, Section 5 summarizes the main findings, highlighting the improvements in predictive fidelity, physical interpretability, and design implications for vibration mitigation and occupant comfort.

2. Dynamic Formulation and Numerical Solution of the 8-DOF Occupant-Wheelchair System.

2.1. The 8-DOF human-wheelchair model. The vertical vibration behavior of the occupant-wheelchair system is represented by an 8-DOF lumped-parameter model comprising seven physical masses and one equivalent seat-cushion subsystem. Each mass corresponds to a distinct structural or anatomical segment, including the head, upper torso, lower torso, seat pan, cushion, rear wheel assembly, and chassis. Linear spring-damper pairs connect adjacent masses, forming continuous pathways for elastic energy transfer and viscous dissipation throughout the seated posture [27, 28, 29]. Figure 1 illustrates the coupling architecture of the model along the vertical axis of motion transmission.

2.2. Subsystem representation and parameter definition. The occupant-wheelchair vibration model is formulated as an integrated 8-DOF coupled system that links the mechanical structure of the wheelchair with the biomechanical components of the seated occupant. Each degree of freedom represents a lumped mass connected by stiffness and damping elements that describe energy transfer and deformation under vertical excitation. The system is conceptually separated into two interacting domains, the wheelchair subsystems and the occupant subsystems, which are dynamically coupled through the seat-cushion interface as illustrated in Figure 1.

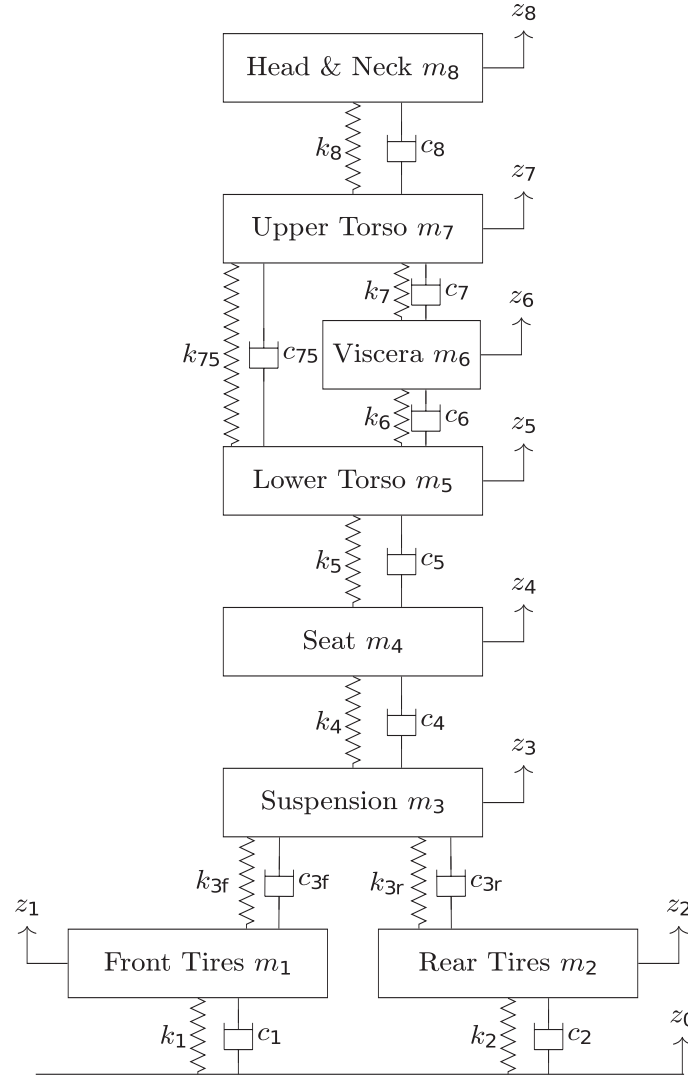


FIGURE 1. Lumped-parameter 8-DOF occupant-wheelchair vibration model subjected to vertical base excitation

2.2.1. Wheelchair subsystems. Wheelchair subsystems are represented by masses m_1 to m_4 with corresponding damping coefficients c_1 to c_4 and stiffness coefficients k_1 to k_4 . The front tires defined by (m_1, c_1, k_1) simulate the viscoelastic contact between the front wheel and the ground, absorbing high-frequency irregularities and transmitting the resulting vibration upward. The rear tires characterized by (m_2, c_2, k_2) represent the dominant load-bearing wheels that determine the primary excitation entering the frame. The suspension frame expressed by (m_3, c_3, k_3) models the structural compliance of the chassis, including small material and joint damping effects that shape mid-frequency vibration propagation. The seat cushion corresponding to (m_4, c_4, k_4) functions as a viscoelastic layer mediating vibration transfer from the mechanical structure to the human body, its parameters varying with cushion material, internal air distribution, gel content and foam density.

2.2.2. Occupant subsystems. Occupant subsystems consist of four anatomical segments represented by masses m_5 to m_8 and their associated damping and stiffness coefficients c_5 to c_8 and k_5 to k_8 . The lower torso (m_5, c_5, k_5) encompasses the pelvis and buttock regions that directly interface with the seat and act as the principal channel of vertical load

transfer. The viscera (m_6, c_6, k_6) represent the internal organ cluster capable of oscillating relative to the skeletal frame, providing viscous damping through tissue deformation. The upper torso (m_7, c_7, k_7) describes the thoracic and shoulder region that governs the main body resonance around 3-4 [Hz]. The head-neck complex (m_8, c_8, k_8) corresponds to the cranio-cervical segment that exhibits the highest sensitivity to vertical acceleration and determines overall comfort perception.

Additional coupling parameters are included to preserve mechanical continuity along the frame and spinal column. The elements (c_{3f}, k_{3f}) represent the front branch connecting the suspension to the seat base, whereas (c_{3r}, k_{3r}) denote the rear branch linking the frame to the backrest. The pair (c_{75}, k_{75}) connects the upper and lower torso segments, maintaining realistic energy transmission along the spine. Each parameter group (m_i, c_i, k_i) and coupling pair ensure biomechanical coherence and positive-definite system matrices [27, 29].

2.3. Standard dynamic parameters and cushion-specific variations. To ensure physical consistency across all simulation cases, the principal mass, damping, and stiffness parameters of the 8-DOF occupant-wheelchair system are standardized according to validated anatomical, mechanical, and ISO 2631-1 reference data. Only the seat-cushion subsystem parameters are allowed to vary among cushion models, while all other subsystem properties remained constant throughout the optimization to prevent non-physical parameter drift and maintain biomechanical comparability. Table 1 and Table 2 summarize the fixed baseline parameters and the calibrated cushion-dependent properties, respectively.

The values in Table 1 are fixed during all optimization stages to ensure consistency of the human-wheelchair mechanical baseline, whereas the parameters in Table 2 are iteratively refined using GA, PSO, DE and the Hybrid GA-PSO-DE algorithm. This separation between constant anatomical-structural parameters and variable seat-cushion

TABLE 1. Standard dynamic parameters of the 8-DOF occupant-wheelchair system (baseline standard model)

Component	Mass, m_i [kg]	Equivalent damping	Equivalent dynamic
		coefficient, c_i [N·s/m]	stiffness, k_i [N/m]
Front tire	1.00	500	60,000
Rear tire	1.60	500	6,000
Suspension frame	15.00	$c_{3f} = 700$	$k_{3f} = 13,400$
		$c_{3r} = 700$	$k_{3r} = 74,600$
Seat cushion	1.50	Specified per cushion type (see Table 2)	
Lower torso	36.00	2,475	49,340
Viscera	5.50	330	20,000
Upper torso	15.00	200	10,000
Head-neck complex	4.17	250	134,400
Upper-lower torso joint	—	909.1	192,000

Remark: m_i = lumped mass of the i -th subsystem; c_i, k_i = equivalent damping and stiffness constants, respectively. Subscripts f and r denote front and rear components. A harmonic base excitation amplitude of $\mathbf{Z}_0 = 0.005$ [m] is applied, consistent with ISO 2631-1 guidelines for seated vibration assessment.

TABLE 2. Representative wheelchair seat cushions categorized by material archetype. A fixed equivalent cushion mass of $m_4 = 1.50$ [kg] is used in all simulations.

Material type	Cushion model	Equivalent damping coefficient, c_4 [N·s/m]	Equivalent dynamic stiffness, k_4 [N/m]
Gel-based (fluid-viscous)	Jay J2 Deep Contour	508	36,890
Air-based (pneumatic cell)	ROHO High Profile	688	77,390
Foam-based (viscoelastic)	Comfort Mate Foam	1,149	115,500

Remark: c_4 quantifies the viscoelastic energy dissipation governing vibration damping and comfort, whereas k_4 expresses the elastic restoring stiffness that controls vertical transmissibility. Together, these parameters define the dynamic seat-occupant coupling behavior within the 8-DOF vibration model.

properties provides a rigorous and fair foundation for comparative optimization, enabling the transmissibility and phase response differences to be attributed solely to cushion viscoelastic characteristics rather than systemic parameter drift.

2.4. Mechanical property identification. The standard mechanical parameters of the occupant-wheelchair system are defined from validated biomechanical and anatomical literature, ensuring that all physical constants represent realistic structural and tissue-level properties [3, 30]. These reference values provide a consistent basis for vibration modeling, allowing direct comparison with established seated human biodynamic studies. All parameters follow the conventions specified in ISO 2631-1:1997 [26], which standardizes vibration exposure assessment for seated occupants.

Table 1 presents the standard lumped parameters for the 8-DOF occupant-wheelchair system. Each term corresponds to the equivalent mass, damping, and stiffness of the associated mechanical or anatomical component, including the front and rear tires, suspension frame, seat cushion, and body segments (lower torso, viscera, upper torso, and head-neck complex). This parameterization ensures physical interpretability and consistency across multibody vibration models.

The parameters summarized in Table 2 represent standard reference values for commercial wheelchair seat cushions widely used in vibration and comfort studies. They are compiled from published experimental databases and manufacturer specifications under quasi-static and low-frequency loading conditions. Using these standardized values allows the present model to remain compatible with benchmark datasets in seated vibration analysis and to ensure traceability across future model validation studies.

2.5. Matrix equation of motion. The coupled vibration behavior of the integrated 8-DOF occupant-wheelchair system is governed by the general matrix equation of motion

$$\mathbf{M}\ddot{\mathbf{z}}(t) + \mathbf{C}\dot{\mathbf{z}}(t) + \mathbf{K}\mathbf{z}(t) = \mathbf{F}(t), \quad (1)$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ represent the global mass, damping, and stiffness matrices that encapsulate the coupled dynamics of the mechanical and anatomical subsystems. The vector $\mathbf{z}(t)$ contains the vertical displacements of all eight lumped masses, and $\mathbf{F}(t)$ denotes the base excitation transmitted from the tire-ground interface to the chassis and seat structure. Each matrix incorporates distinct physical mechanisms that collectively describe the full dynamic interaction shown in Figure 1. The mass matrix $\mathbf{M}$ represents

the inertial distribution of the wheelchair-occupant system, linking the front and rear tires, suspension frame, seat cushion, and the four anatomical segments of the occupant. The damping matrix $\mathbf{C}$ describes energy dissipation due to viscous and hysteretic effects occurring in pneumatic components, seat materials, and biological tissues. The stiffness matrix $\mathbf{K}$ defines the elastic restoring forces that couple adjacent masses, characterizing both mechanical compliance and biomechanical rigidity along the vibration path from the ground to the head-neck complex [27, 28].

The assembled system matrices satisfy symmetry and positive-definiteness conditions, ensuring physically realistic energy transfer and numerical stability in both time- and frequency-domain simulations. Ground excitation is applied at the tire level, while the base node is constrained to a fixed boundary representing the rigid road surface. Initial conditions assume zero displacement and velocity to isolate steady-state harmonic responses. The explicit block formulations of $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are consistent with the structural definitions introduced in Section 2.2 and are expanded analytically in (8)-(33). This unified matrix framework enables precise computation of vibration transmissibility, phase response, and resonance behavior for each seat-occupant configuration under controlled experimental or simulated excitation.

2.6. Frequency-domain transformation. Assuming a steady harmonic base excitation with angular frequency ω and amplitude A , the steady-state displacement response can be expressed as

$$\mathbf{z}(t) = \Re [\mathbf{Z}(j\omega) e^{j\omega t}], \quad (2)$$

where $\mathbf{Z}(j\omega)$ represents the complex amplitude vector of the system response.

Substituting (2) into (1) yields the frequency-domain equilibrium relation:

$$[-\omega^2 \mathbf{M} + j\omega \mathbf{C} + \mathbf{K}] \mathbf{Z}(j\omega) = \mathbf{F}(j\omega), \quad (3)$$

where the term in brackets defines the dynamic stiffness matrix, given by

$$\mathbf{Q}(j\omega) = -\omega^2 \mathbf{M} + j\omega \mathbf{C} + \mathbf{K}, \quad (4)$$

$\mathbf{Q}(j\omega)$ acts as the complex impedance operator linking excitation and response under harmonic base vibration. The external excitation force vector corresponding to the base motion is described as

$$\mathbf{F}(j\omega) = (\mathbf{K}_{\text{in}} + j\omega \mathbf{C}_{\text{in}}) \mathbf{Z}_0(j\omega), \quad (5)$$

where $\mathbf{Z}_0(j\omega)$ denotes the base-excitation amplitude (typically the vertical displacement amplitude at the wheel-ground interface), $\mathbf{K}_{\text{in}}$ and $\mathbf{C}_{\text{in}}$ are the input stiffness and damping coupling vectors, respectively, and defined as

$$\mathbf{K}_{\text{in}} = [k_1 \quad k_2 \quad 0 \quad \cdots \quad 0]^T \quad (6)$$

$$\mathbf{C}_{\text{in}} = [c_1 \quad c_2 \quad 0 \quad \cdots \quad 0]^T, \quad (7)$$

which represent the direct stiffness and damping transmission pathways conveying vibration from the front and rear wheel assemblies into the system [27, 28, 29].

2.7. Expanded 8×8 frequency-domain representation. To provide an explicit formulation of the coupled dynamics, the steady-state frequency-domain balance in (3) is expanded for the complete occupant-wheelchair system comprising 8-DOFs. This representation captures the distributed inertial, damping, and stiffness interactions among the wheelchair's structural subsystems and the occupant's anatomical components in a unified linear framework. The general form can be written as

$$\mathbf{A}(j\omega) \mathbf{Z}(j\omega) = \mathbf{K}_{\text{in}}(j\omega) \mathbf{Z}_0(j\omega), \quad (8)$$

where $\mathbf{A}(j\omega) \in \mathbb{C}^{8 \times 8}$ represents the full system impedance matrix, $\mathbf{Z}(j\omega) = [Z_1, \dots, Z_8]^T$ denotes the complex displacement responses of each DOF, and $\mathbf{K}_{in}(j\omega)\mathbf{Z}_0(j\omega)$ defines the applied harmonic excitation at the base node. Expanding (8) yields

$$\begin{aligned}
 & \begin{bmatrix} A_1(j\omega) & 0 & A_2(j\omega) & 0 & 0 & 0 & 0 & 0 \\ 0 & B_1(j\omega) & B_2(j\omega) & 0 & 0 & 0 & 0 & 0 \\ C_1(j\omega) & C_2(j\omega) & C_3(j\omega) & C_4(j\omega) & 0 & 0 & 0 & 0 \\ 0 & 0 & D_1(j\omega) & D_2(j\omega) & D_3(j\omega) & 0 & 0 & 0 \\ 0 & 0 & 0 & E_1(j\omega) & E_2(j\omega) & E_3(j\omega) & 0 & 0 \\ 0 & 0 & 0 & 0 & F_1(j\omega) & F_2(j\omega) & F_3(j\omega) & 0 \\ 0 & 0 & 0 & 0 & 0 & G_1(j\omega) & G_2(j\omega) & G_3(j\omega) \\ 0 & 0 & 0 & 0 & 0 & 0 & H_1(j\omega) & H_2(j\omega) \end{bmatrix} \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \\ Z_4 \\ Z_5 \\ Z_6 \\ Z_7 \\ Z_8 \end{bmatrix} \\
 &= \begin{bmatrix} K_1(j\omega) \\ K_2(j\omega) \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{Z}_0(j\omega). \tag{9}
 \end{aligned}$$

Each matrix element $A_1(j\omega)$ through $H_2(j\omega)$ describes the frequency-dependent impedance coupling between adjacent substructures, and are explicitly defined below.

$$A_1(j\omega) = -\omega^2 m_1 + j\omega(c_1 + c_{3f}) + (k_1 + k_{3f}), \tag{10}$$

$$A_2(j\omega) = -j\omega c_{3f} - k_{3f}, \tag{11}$$

$$B_1(j\omega) = -\omega^2 m_2 + j\omega(c_2 + c_{3r}) + (k_2 + k_{3r}), \tag{12}$$

$$B_2(j\omega) = -j\omega c_{3r} - k_{3r}, \tag{13}$$

$$C_1(j\omega) = -j\omega c_{3f} - k_{3f}, \tag{14}$$

$$C_2(j\omega) = -j\omega c_{3r} - k_{3r}, \tag{15}$$

$$C_3(j\omega) = -\omega^2 m_3 + j\omega(c_{3f} + c_{3r} + c_4) + (k_{3f} + k_{3r} + k_4), \tag{16}$$

$$C_4(j\omega) = -j\omega c_4 - k_4, \tag{17}$$

$$D_1(j\omega) = -j\omega c_4 - k_4, \tag{18}$$

$$D_2(j\omega) = -\omega^2 m_4 + j\omega(c_4 + c_5) + (k_4 + k_5), \tag{19}$$

$$D_3(j\omega) = -j\omega c_5 - k_5, \tag{20}$$

$$E_1(j\omega) = -j\omega c_5 - k_5, \tag{21}$$

$$E_2(j\omega) = -\omega^2 m_5 + j\omega(c_5 + c_6 + c_{75}) + (k_5 + k_6 + k_{75}), \tag{22}$$

$$E_3(j\omega) = -j\omega c_6 - k_6, \tag{23}$$

$$F_1(j\omega) = -j\omega c_6 - k_6, \tag{24}$$

$$F_2(j\omega) = -\omega^2 m_6 + j\omega(c_6 + c_7) + (k_6 + k_7), \tag{25}$$

$$F_3(j\omega) = -j\omega c_7 - k_7, \tag{26}$$

$$G_3(j\omega) = -\omega^2 m_7 + j\omega(c_7 + c_8 + c_{75}) + (k_7 + k_8 + k_{75}), \tag{27}$$

$$G_2(j\omega) = -j\omega c_7 - k_7, \tag{28}$$

$$G_1(j\omega) = -j\omega c_{75} - k_{75}, \tag{29}$$

$$H_1(j\omega) = -j\omega c_8 - k_8, \tag{30}$$

$$H_2(j\omega) = -\omega^2 m_8 + j\omega c_8 + k_8, \tag{31}$$

$$K_1(j\omega) = j\omega c_1 + k_1, \quad (32)$$

and

$$K_2(j\omega) = j\omega c_2 + k_2. \quad (33)$$

Equations (8) and (9) therefore provide a complete, frequency-resolved impedance representation of the interconnected human-wheelchair system, allowing direct computation of transmissibility, phase lag, and modal participation across the 2-20 [Hz] excitation spectrum. Furthermore, (8)-(33) establish a comprehensive frequency-domain impedance model of the coupled human-wheelchair system. This expanded matrix form offers a direct analytical framework for evaluating seat transmissibility, phase lag, and modal participation within the 2-20 [Hz] excitation spectrum. By retaining all physical couplings and complex-valued interactions, the formulation enables precise computation of resonance frequencies, modal energy transfer, and damping efficiency – forming the analytical foundation for parameter identification, system optimization, and model validation.

2.8. Numerical frequency-domain solution. For each discrete excitation frequency $f_i = \omega_i/(2\pi)$ in the range 0-20 [Hz], the steady-state response is obtained from the frequency-domain equilibrium:

$$\mathbf{Z}(j\omega_i) = \mathbf{Q}^{-1}(j\omega_i) \mathbf{F}(j\omega_i) \quad (i = 1, 2, \dots, N_f), \quad (34)$$

where $\mathbf{Q}^{-1}(j\omega_i)$ is the frequency-dependent compliance matrix defined in (4). This direct matrix-inversion method ensures numerical stability and preserves the coupled inertial, damping, and elastic interactions of the entire 8-DOF system at each excitation frequency. The resulting complex displacement vector $\mathbf{Z}(j\omega_i)$ describes the motion of all DOFs. The dynamic transfer of vibration from the chassis to the seat is quantified by the magnitude and phase ratio between the 5th and 4th coordinates.

2.9. Definition of transmissibility and phase response. The vibration transfer from the wheelchair seat to the occupant is quantified by the transmissibility magnitude and corresponding phase angle, defined between the *seat base* (Z_4) and the *lower torso-seat interface* (Z_5) as illustrated in Figure 1. This input-output pair directly represents the vibration transmitted from the seat structure to the occupant's lower torso and is therefore adopted as the primary descriptor of ride comfort in accordance with ISO 2631-1.

At each discrete excitation frequency ω_i [rad/s] (equivalently $f_i = \omega_i/2\pi$ [Hz]), the transmissibility magnitude $T_j(j\omega_i)$ and phase angle $\phi_j(j\omega_i)$ for seat cushion configuration j are defined as

$$T_j(j\omega_i) = \left| \frac{Z_5(j\omega_i)}{Z_4(j\omega_i)} \right|, \quad \phi_j(j\omega_i) = \arg \left(\frac{Z_5(j\omega_i)}{Z_4(j\omega_i)} \right), \quad (35)$$

where $Z_4(j\omega_i)$ and $Z_5(j\omega_i)$ denote the complex displacement amplitudes of the seat base and the lower torso-seat interface, respectively, at the i -th excitation frequency ω_i [rad/s]. Accordingly, $T_j(j\omega_i)$ is a dimensionless transmissibility magnitude, and $\phi_j(j\omega_i)$ represents the corresponding phase shift expressed in degrees [°].

A transmissibility value $T_j(j\omega_i) > 1$ indicates vibration amplification at the occupant interface, whereas $T_j(j\omega_i) < 1$ signifies attenuation due to the viscoelastic damping of the seat cushion. The phase angle $\phi_j(j\omega_i)$ characterizes the relative motion between the seat and the occupant: $\phi_j(j\omega_i) \approx 0$ [°] corresponds to nearly in-phase motion (rigid-body behaviour), while $\phi_j(j\omega_i) \approx -90$ [°] represents a viscous-dominated response associated with maximum energy dissipation. Both magnitude and phase responses are evaluated within the frequency range of 0-20 [Hz], which encompasses the dominant excitation band for vertical human-wheelchair vibration.

2.10. Model interpretation and dynamic coupling insight. The frequency-domain formulation in (34) unifies the physical and numerical representations of the human-wheelchair system, providing a coupled biomechanical interpretation consistent with established seated-vibration frameworks [1, 2, 3]. Through the compliance operator $\mathbf{Q}^{-1}(j\omega)$, the formulation couples the distributed mass, viscous damping, and elastic stiffness within a single spectral framework, as previously demonstrated in biomechanical multibody modeling studies [15, 16]. This formulation captures both the low-frequency quasi-static deformation and the high-frequency resonant behavior of the seat-frame-occupant assembly without oversimplifying the dynamic coupling observed in experimental wheelchair investigations [12, 14]. Accordingly, the approach resolves the coupled dynamics within the critical 2-6 [Hz] band – recognized as the dominant region of human body resonance – enabling accurate prediction of transmissibility peaks, phase reversals, and damping efficiency [1, 17].

2.11. Inverse parameter identification framework. Baseline values of the global matrices $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are obtained from measured mechanical and anthropometric data representing a 50th-percentile adult male and the tested wheelchair configuration [2, 14]. Because the seat-cushion subsystem exhibits viscoelastic and frequency-dependent behavior [7, 8], its effective stiffness and damping coefficients are refined through inverse identification using experimentally measured transmissibility data [5, 10].

The optimization objective minimized the weighted squared deviation between the simulated and experimental transmissibility magnitudes:

$$J = \sum_{i=1}^{N_f} [w_i(T_{\text{sim}}(j\omega_i) - T_{\text{exp}}(j\omega_i))]^2, \quad (36)$$

where $T_{\text{sim}}(j\omega_i)$ and $T_{\text{exp}}(j\omega_i)$ denote simulated and measured transmissibility at frequency ω_i [rad/s], respectively. The weighting factor w_i emphasizes the 2-6 [Hz] frequency range that dominates human biodynamic sensitivity and ride comfort in accordance with ISO 2631-1 and prior studies [1, 3]. Minimization of J yields physically consistent and dynamically stable damping and stiffness parameters for each seat-cushion configuration. This inverse identification framework ensures biomechanical realism, numerical robustness, and reproducibility, providing a calibrated foundation for global optimization via GA [23], PSO [24], DE [25], and the staged Hybrid GA-PSO-DE algorithm.

2.12. Physical constraints, positive definiteness and damping validity. To guarantee that each candidate parameter set corresponds to a physically realizable mechanical system, the stiffness and damping matrices are verified at every iteration before cost-function evaluation, following the conditioning strategies recommended in seated vibration analysis [3, 17]. These verifications prevent non-physical vibration modes and enhance numerical stability throughout the optimization.

1) Stiffness positive definiteness

The stiffness matrix $\mathbf{K}$ must remain positive definite to ensure real natural frequencies and non-negative strain energy, consistent with structural dynamics principles in prior biomechanical modeling studies [15, 16]. A Cholesky feasibility test is applied to verifying

$$\lambda_{\min}(\mathbf{K}) > 0, \quad (37)$$

where $\lambda_{\min}$ is the smallest eigenvalue of $\mathbf{K}$. If any eigenvalue is zero or negative, the matrix is reconstructed as a positive-definite form $\mathbf{K}_{\text{pd}}$ using spectral decomposition

$$\mathbf{K}_{\text{pd}} = \mathbf{V} \text{diag}(\max(\lambda_i, \epsilon)) \mathbf{V}^T, \quad \epsilon = 10^{-6}, \quad (38)$$

where $\mathbf{K} = \mathbf{V} \text{diag}(\lambda_i) \mathbf{V}^\top$. The corrected matrix $\mathbf{K}_{\text{pd}}$ is then used in the subsequent frequency-response computation [14].

2) Damping physicality

To maintain dissipative behavior, the damping matrix $\mathbf{C}$ must yield strictly positive modal damping ratios, reflecting the viscoelastic characteristics reported in seat-occupant vibration studies [7, 8]. At the dominant resonance frequency ω_{pk} , the impedance matrix is

$$\mathbf{Q}(j\omega) = -\omega^2 \mathbf{M} + j\omega \mathbf{C} + \mathbf{K}, \quad (39)$$

and the modal damping ratio for mode r is

$$\zeta_r = \frac{\phi_r^\top \mathbf{C} \phi_r}{2\sqrt{(\phi_r^\top \mathbf{K} \phi_r)(\phi_r^\top \mathbf{M} \phi_r)}}. \quad (40)$$

If $\zeta_r \leq 0$, element-wise positivity is enforced as

$$\mathbf{C}_{\text{pos}} = |\mathbf{C}|, \quad (41)$$

ensuring positive damping consistent with physical observations of energy dissipation in seat-cushion mechanics [8, 16].

3) Constraint enforcement

Both $\mathbf{K}_{\text{pd}}$ and $\mathbf{C}_{\text{pos}}$ are applied only when violations are detected. This adaptive correction preserved mechanical stability and positive energy storage throughout optimization [1, 3].

4) Numerical conditioning criterion (**rcond**)

During frequency-response computation, the reciprocal condition number (**rcond**) of $\mathbf{Z}$ is monitored at every frequency step:

$$\text{rcond}(\mathbf{Z}) = \frac{1}{\kappa(\mathbf{Z})} = \frac{\sigma_{\min}(\mathbf{Z})}{\sigma_{\max}(\mathbf{Z})}, \quad (42)$$

where $\kappa(\mathbf{Z})$ is the condition number, and $\sigma_{\min}$, $\sigma_{\max}$ denote the minimum and maximum singular values. If $\text{rcond}(\mathbf{Z}) < 10^{-8}$, indicating potential ill-conditioning, a small diagonal term is added to stabilize inversion, consistent with numerical vibration techniques [23, 24]:

$$\mathbf{Z}_{\text{reg}}(j\omega) = \mathbf{Z}(j\omega) + 10^{-6} \mathbf{I}. \quad (43)$$

A denominator tolerance of 10^{-12} is also applied in the transmissibility definition to prevent overflow when $|Y_4|$ approaches zero:

$$T(j\omega_i) = \frac{|Z_5(j\omega_i)|}{\max(|Z_4(j\omega_i)|, 10^{-12})}. \quad (44)$$

The combined safeguards of (37)-(44) ensure physically valid, dissipative, and numerically stable parameter sets. Consequently, the simulated transmissibility curves $T(j\omega_i)$ remain smooth and consistent across the entire 0-20 [Hz] excitation range, accurately reflecting the seated-human vibration characteristics reported in prior experimental studies [3, 16, 17].

3. Metaheuristic Optimization Framework. A unified metaheuristic optimization framework is developed to identify the stiffness and damping parameters governing the dynamic response of the 8-DOF occupant-wheelchair system. This framework integrates four complementary algorithms – Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, and a staged Hybrid GA-PSO-DE – to balance global exploration, adaptive convergence, and precision refinement in a biomechanically interpretable parameter space.

All methods minimized an identical objective function representing the weighted error between simulated and experimental vibration transmissibility, evaluated on a frequency grid from 0 to 20 [Hz]. By employing consistent design-variable definitions, physical constraints, and weighting functions, the framework ensured fair comparison, reproducibility, and numerical stability across optimization methods. The four algorithms each contributed unique strengths to the parameter identification process, as detailed below.

3.1. Unified problem definition and objective. All optimization algorithms operate on the same problem formulation to ensure numerical consistency and physical comparability across methods.

3.1.1. Design variables (27 total). The parameters to be identified include the lumped masses (m_i), damping coefficients (c_i), and stiffness constants (k_i) of the combined wheelchair-occupant vibration system. These variables represent both the structural components of the wheelchair (wheels, frame, seat) and the anatomical segments of the occupant (head & neck, upper torso, viscera, lower torso) that jointly determine vibration transmissibility. The complete design-variable vector is expressed as

$$\mathbf{x} = \begin{bmatrix} m_1 & m_2 & m_3 & m_5 & m_6 & m_7 & m_8 & c_1 & c_2 & c_3 & c_5 & c_6 & c_7 & c_8 & c_{3f} & c_{3r} & c_{75} \\ k_1 & k_2 & k_3 & k_5 & k_6 & k_7 & k_8 & k_{3f} & k_{3r} & k_{75} \end{bmatrix}^T. \quad (45)$$

This excludes the seat-cushion mass m_4 , which is treated as a constant in all configurations, and explicitly includes the coupling elements (c_{3f}, c_{3r}, c_{75}) and (k_{3f}, k_{3r}, k_{75}) that link structural and anatomical subsystems.

3.1.2. Feasible bounds. Each variable is constrained within physically realistic limits to maintain biomechanical plausibility:

$$\begin{aligned} m_i &\in [0.8, 1.9] \text{ [kg]}, \\ c_i &\in [150, 1500] \text{ [N}\cdot\text{s/m]}, \\ k_i &\in [5 \times 10^3, 1.5 \times 10^5] \text{ [N/m]}. \end{aligned} \quad (46)$$

These limits encompass the dynamic ranges reported in multi-DOF seated-human vibration models [3]. Human segment masses typically fall within 1-20 [kg], while structural stiffness values generally range from 10^3 to 10^5 [N/m], and equivalent viscous damping coefficients are typically on the order of 10^2 to 10^3 [N·s/m]. By restricting the search to these physically verified ranges – consistent with ISO 2631-1 comfort guidelines – the optimization process avoids non-physical parameter values and ensures biomechanical plausibility.

3.1.3. Biomechanical constraints. To preserve anatomical realism, all human-body segment parameters (m_5 - m_8 and their corresponding c_i, k_i) are held constant across all cases, ensuring that occupant physiology remains unchanged among seat configurations. Only the seat-cushion parameters (c_4, k_4) are varied between configurations A-C, representing seven commercial cushion types. The pre-calibrated damping and stiffness constants (c_4, k_4) are obtained from experimental dynamic measurements by Garcia-Mendez et al. [18], conducted under standardized laboratory conditions using a seat-loading apparatus. These data reflect the true viscoelastic behavior of each cushion model – (A) Jay J2 Deep Contour (gel-based), (B) ROHO High Profile (air-based), and (C) Comfort Mate Foam (foam-based) – ensuring physical consistency throughout all optimization processes.

3.1.4. Objective function. All algorithms minimized a weighted least-squares cost between simulated and experimental transmissibility curves:

$$J = \sum_{i=1}^{N_f} W(j\omega_i) [T_{\text{sim}}(j\omega_i) - T_{\text{exp}}(j\omega_i)]^2, \quad (47)$$

where $T_{\text{sim}}(j\omega_i) = |Z_5(j\omega_i)|/|Z_4(j\omega_i)|$ is the simulated transmissibility magnitude (ratio of occupant to seat-base response at frequency ω_i), and $T_{\text{exp}}(j\omega_i)$ denotes the corresponding experimental measurement. The summation spans $N_f = 50$ frequency points uniformly distributed between 0-20 [Hz], covering the principal vibration band relevant to seated occupants.

3.1.5. Frequency weighting function. A custom weighting function $W(j\omega)$ is employed to emphasize frequencies critical to human comfort and biomechanical resonance:

$$W(j\omega_i) = [1 + w_{\text{band}} \mathbb{I}_{[2,6]}(j\omega_i)] \left[1 + w_{\text{peak}} \exp \left(-\frac{1}{2} \left(\frac{j\omega_i - j\omega_{\text{pk}}}{\sigma_H} \right)^2 \right) \right], \quad (48)$$

where $\mathbb{I}_{[2,6]}(j\omega_i)$ is an indicator function equal to 1 for $\omega \in [2, 6]$ [Hz] and 0 otherwise, $w_{\text{band}} = 2.0$, $w_{\text{peak}} = 3.0$, and $\sigma_H = 0.6$ [Hz]. This assigns double weight to the 2-6 [Hz] frequency band – the dominant resonance region of the human lower torso and seat – and an additional Gaussian weighting centered at the experimentally observed peak frequency $j\omega_{\text{pk}}$. Such weighting prioritizes accurate fitting in the physiologically sensitive range, consistent with ISO 2631-1 and comfort-weighted analyses [1, 3].

3.1.6. Dynamic simulation. For a given parameter vector $\mathbf{x}$, the steady-state frequency response is obtained by solving the frequency-domain equilibrium equation:

$$\mathbf{Z}(j\omega) = [-\omega^2 \mathbf{M} + j\omega \mathbf{C} + \mathbf{K}]^{-1} \mathbf{F}(j\omega), \quad (49)$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ denote the global mass, damping, and stiffness matrices, respectively, and $\mathbf{F}(j\omega)$ is the excitation vector corresponding to a harmonic base displacement amplitude $A = 0.005$ (m), following ISO 2631-1 moderate exposure levels. The transmissibility is then computed as $T_{\text{sim}}(j\omega) = |Z_5(j\omega)|/|Z_4(j\omega)|$. To ensure numerical stability, the reciprocal condition number of the dynamic stiffness matrix is monitored; if $\text{rcond} < 10^{-8}$, a small regularization term ($10^{-6} \mathbf{I}$) is added to prevent ill-conditioning near resonance.

3.1.7. Physical feasibility checks. At every iteration, each candidate parameter set is validated to guarantee physical realizability: i) Positive-definite stiffness: $\mathbf{K}$ must satisfy $\lambda_{\min}(\mathbf{K}) > 0$, ensuring real natural frequencies and stable equilibrium; ii) Positive damping: all diagonal elements of $\mathbf{C}$ are required to be non-negative, ensuring dissipative behavior and energy decay. If violations occurred, a spectral correction is applied to project $\mathbf{K}$ and $\mathbf{C}$ back into their positive-definite and positive-semidefinite domains, preserving mechanical validity and stability throughout the optimization process.

3.1.8. Convergence criteria. Each optimization algorithm employed a relative convergence tolerance to determine termination:

$$\frac{|J_{k+1} - J_k|}{J_k} < 10^{-6}. \quad (50)$$

If this condition is satisfied for a predefined number of consecutive generations or iterations (typically five for GA, twenty-five for PSO, and ten for DE), the search is terminated. A maximum iteration cap is also enforced to prevent indefinite execution [23, 24, 25].

3.1.9. Local refinement. Following global optimization (GA, PSO, DE, or Hybrid sequence), a bounded local search is applied using a Nelder-Mead simplex algorithm (`fminsearch` in MATLAB). To handle variable bounds, a logistic transformation is introduced:

$$z = \ln \left(\frac{x - x_{\min}}{x_{\max} - x} \right), \quad (51)$$

which maps the finite domain $[x_{\min}, x_{\max}]$ to an unbounded z -space. The optimizer operates in z for improved conditioning and maps back to x after convergence [23, 24]. The refined solution is validated for positive-definite $\mathbf{K}$ and non-negative damping before acceptance.

3.1.10. Reproducibility. Each algorithm is executed multiple times under identical initialization and random-seed conditions to verify consistency of the final solution. Repeated trials with varied seeds confirmed convergence to the same or statistically equivalent minima, demonstrating algorithmic robustness and stability of the identified vibration parameters [3, 16, 23].

With this unified framework established, the following subsections detail the specific implementation and characteristics of each optimization algorithm.

3.2. Genetic Algorithm approach. GA is employed as a population-based global search strategy to explore the complex, high-dimensional parameter space of the 8-DOF occupant-wheelchair model. By mimicking the process of natural selection, GA iteratively evolves a population of candidate parameter sets over successive generations to minimize the transmissibility error cost function defined in (47).

3.2.1. Initialization. A population of $N_p = 40$ individuals, each representing a complete 27-parameter vector $\mathbf{x}$, is initialized uniformly at random within the feasible bounds defined in (46). This ensured broad coverage of the parameter domain. Each initial candidate solution is validated against the mechanical feasibility criteria (positive-definite $\mathbf{K}$ and non-negative damping coefficients in $\mathbf{C}$) before cost evaluation to eliminate unstable or non-physical configurations.

3.2.2. Evolutionary operators. At each generation, GA applied three fundamental operators – selection, crossover, and mutation – to producing new offspring populations from the current pool of solutions.

Selection. Tournament selection (size = 2) is adopted, where two individuals are randomly chosen, and the one with the lower cost J is selected as a parent. This approach favors fitter individuals while preserving stochastic diversity within the population.

Crossover. A uniform crossover scheme with probability $p_c = 0.5$ per gene is applied to each pair of parents. Each parameter of the offspring is independently chosen from one of the two parents with equal probability, effectively recombining parental traits and enabling exploration of new parameter regions.

Mutation. Following crossover, random-reset mutation is performed with a probability $p_m = 0.15$ per gene. Each mutated parameter is reassigned to a new random value within its feasible range in (46), thereby introducing novel traits and preventing premature convergence.

Elitism. To preserve the best-performing solutions, the top $n_{\text{elite}} = 2$ individuals from each generation are copied directly to the next generation. This guaranteed monotonic improvement of the best fitness value across generations.

3.2.3. Generational evolution and convergence. The GA is executed for a maximum of $N_g = 100$ generations. In each generation, after the application of genetic operators, the cost J_{GA} is evaluated for all individuals using the transmissibility-based objective function in (47). The best cost at generation k , denoted $J_{\text{GA}}^{(k)}$, is recorded and used to monitor convergence. The relative improvement criterion

$$\frac{|J_{\text{GA}}^{(k+1)} - J_{\text{GA}}^{(k)}|}{J_{\text{GA}}^{(k)}} < 10^{-6} \quad (52)$$

had to hold for five consecutive generations before the algorithm is terminated early. In most runs, GA convergence is achieved before the 100-generation cap.

3.2.4. Local refinement. Upon convergence, the best solution $\mathbf{x}_{\text{GA}}^*$ underwent local refinement using the bounded Nelder-Mead simplex search described in Section 3.1. The logistic transformation in (51) ensured the refined parameters remained within the feasible domain. This step provided additional fine-tuning of damping and stiffness parameters to further reduce J while maintaining physical realism.

3.2.5. Outcome and verification. The final GA-optimized parameter vector $\mathbf{x}_{\text{GA}}^*$ is verified against the positive-definiteness and damping-positivity conditions in (37)-(44). Because the GA is constrained by the feasible bounds throughout, all resulting matrices $\mathbf{K}$ and $\mathbf{C}$ remained physically valid. The algorithm consistently identified multiple distinct yet biomechanically plausible minima, allowing comparison across parameter sets to ensure realism (e.g., avoiding unrealistically high damping or stiffness magnitudes). GA thus proved highly effective in globally exploring the nonlinear search space, preventing local entrapment, and yielding physically consistent parameter configurations aligned with seat-occupant transmissibility characteristics.

Implementation Notes. The GA hyperparameters – population size of 40, mutation rate of 15[%], crossover probability of 0.5, and elitism of two individuals – are tuned following best practices in seat-occupant vibration optimization [14, 16]. This configuration provided a robust trade-off between search diversity and convergence speed.

3.3. Particle Swarm Optimization approach. PSO is applied as a cooperative, population-based metaheuristic that leverages swarm intelligence to identifying the optimal damping and stiffness parameters of the 8-DOF system. Each candidate solution corresponds to a “particle” that adjusts its trajectory based on its own experience and that of the swarm, balancing exploration and exploitation across the search space.

3.3.1. Encoding and swarm initialization. Each particle’s position vector $\mathbf{x}_i$ represented a 27-dimensional candidate parameter set. A swarm of $N_s = 60$ particles is initialized with random positions uniformly distributed within the feasible bounds in (46). Initial velocities $\mathbf{v}_i^{(0)}$ are assigned as small random values up to ± 10 [%] of each parameter range to promote gentle early exploration. All initial particles satisfied the same physical constraints as in the GA method. The initial cost J_{PSO} is computed for all particles to establish their personal and global bests.

3.3.2. Velocity and position update rules. At each iteration t , the position and velocity of each particle i are updated according to the canonical PSO formulation:

$$\mathbf{v}_i^{(t+1)} = w \mathbf{v}_i^{(t)} + c_1 r_1 (\mathbf{p}_i - \mathbf{x}_i^{(t)}) + c_2 r_2 (\mathbf{g} - \mathbf{x}_i^{(t)}), \quad (53)$$

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \mathbf{v}_i^{(t+1)}, \quad (54)$$

where $\mathbf{p}_i$ and $\mathbf{g}$ denote the personal and global best positions, respectively, and $r_1, r_2 \sim \mathcal{U}(0, 1)$ are uniformly distributed random numbers introducing stochasticity.

3.3.3. Adaptive coefficients and velocity control. The algorithm employed an adaptive parameter schedule for improved performance:

- Inertia weight: w decreased linearly from $w_{\text{max}} = 0.9$ to $w_{\text{min}} = 0.35$.

- Cognitive coefficient: c_1 decreased from 2.2 to 1.2.
- Social coefficient: c_2 increased from 1.4 to 2.0.

This adaptive control allowed early exploration dominated by individual learning, followed by later convergence around the swarm's global knowledge. The velocity magnitude in each dimension is clamped by

$$\mathbf{v}_{\max} = 0.25(\mathbf{x}_{\max} - \mathbf{x}_{\min}), \quad (55)$$

limiting step size to 25[%] of the parameter range and preventing divergence.

3.3.4. Boundary handling. If a particle exceeded its feasible range in any dimension, a mirror reflection is applied:

$$x_{i,j}^{(t+1)} = \begin{cases} x_{\max,j} - (x_{i,j}^{(t+1)} - x_{\max,j}), & \text{if } x_{i,j}^{(t+1)} > x_{\max,j} \\ x_{\min,j} + (x_{i,j}^{(t+1)} - x_{\min,j}), & \text{if } x_{i,j}^{(t+1)} < x_{\min,j} \end{cases}, \quad (56)$$

ensuring all parameters remained physically admissible while maintaining search momentum near the boundaries.

3.3.5. Iteration and convergence criteria. The PSO evolved over a maximum of 150 iterations. After each update, the cost J_{PSO} is recalculated for all particles, updating $\mathbf{p}_i$ and $\mathbf{g}$ accordingly. Convergence is achieved when the relative change in the global best cost satisfied

$$\frac{|J_{\text{PSO}}^{(t+1)} - J_{\text{PSO}}^{(t)}|}{J_{\text{PSO}}^{(t)}} < 10^{-6}. \quad (57)$$

3.3.6. Stagnation detection and diversity preservation. To mitigate premature convergence, the algorithm tracked cost stagnation. If the global best cost did not improve beyond 10^{-6} for 25 consecutive iterations, 25[%] of the lowest-performing particles are reinitialized randomly within the search domain. This diversity-preservation mechanism, following the recommendations of [23], enabled recovery from local minima and enhanced robustness.

3.3.7. Local refinement. After global convergence, the globally best particle $\mathbf{g}$ is refined using the same bounded Nelder-Mead local search (Section 3.1). The logistic mapping transformation in (51) prevented boundary locking and ensured feasibility throughout the refinement.

3.3.8. Results and validation. The final PSO-optimized parameter vector $\mathbf{x}_{\text{PSO}}^*$ is validated against the same physical feasibility criteria used for GA. PSO achieved fast convergence and reliably captured the correct resonance-related stiffness and damping parameters, particularly in the 3-5 [Hz] region that dominates seated human response. Adaptive parameter scheduling ensured smooth transitions between exploratory and exploitative phases, while the stagnation-control mechanism provided resilience against local minima. Repeated PSO runs under identical and varied seeds demonstrated consistent convergence to near-identical minima, confirming robustness and reproducibility. Compared with GA, PSO typically required fewer function evaluations but occasionally benefited from diversity reinitialization to match GA's global optimality. Overall, PSO efficiently balanced convergence speed and physical fidelity in identifying biomechanically consistent parameters [16, 17].

3.4. Differential Evolution approach. DE is a population-based metaheuristic designed for continuous parameter spaces. It is selected for its simplicity, robustness, and strong local refinement capability when exploring correlated parameters such as stiffness and damping within the 8-DOF occupant-wheelchair model. DE evolves a population of candidate parameter vectors by generating new solutions through scaled differential perturbations between existing individuals.

3.4.1. Population initialization. A population of $N_{\text{pop}} = 40$ individuals is initialized, each corresponding to a 27-dimensional vector $\mathbf{x}$ within the feasible bounds in (46). All individuals satisfied physical constraints, with body-segment parameters fixed per cushion and seat-cushion parameters (c_4 , k_4) preset from experimental data. Each individual's initial cost J_{DE} is evaluated using the transmissibility-based objective function in (47).

3.4.2. DE strategy. The DE algorithm employed the canonical *DE/rand/1/bin* scheme [25], a well-established and computationally efficient variant widely used in nonlinear system identification and vibration parameter estimation [23, 24]. This notation specifies the generation process of new candidate solutions in each iteration: “DE” denotes the algorithm itself, “rand” indicates that the base vector for mutation is randomly selected from the population to enhance global exploration, “1” denotes the use of a single difference vector to perturb the base vector, providing balanced search diversity, and “bin” refers to the binomial (uniform) crossover mechanism used to merge the mutant and target vectors.

Under this configuration, each trial vector $\mathbf{u}_i$ is generated through three sequential stages – mutation, crossover, and selection – executed within each generation. During mutation, three distinct population members r_1 , r_2 , and r_3 ($\neq i$) are randomly selected to construct a mutant vector as

$$\mathbf{v}_i = \mathbf{x}_{r_1} + F(\mathbf{x}_{r_2} - \mathbf{x}_{r_3}), \quad (58)$$

where $F = 0.7$ is the scaling factor controlling the differential perturbation amplitude. This operation extrapolates from existing population members, enabling the search to explore promising directions in the multidimensional parameter space [23, 25].

Next, the binomial crossover combines the mutant vector $\mathbf{v}_i$ with the target vector $\mathbf{x}_i$ to form a trial vector $\mathbf{u}_i$ according to

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } r_j \leq C_R \text{ or } j = j_{\text{rand}} \\ x_{i,j}, & \text{otherwise} \end{cases}, \quad (59)$$

where $r_j \sim \mathcal{U}(0, 1)$, $C_R = 0.9$ is the crossover probability and j_{rand} ensures that at least one element is inherited from the mutant vector. This recombination process enhances diversity while retaining the continuity of high-quality features from the target vector [24].

Finally, a one-to-one greedy selection strategy retains the fitter individual for the next generation:

$$\mathbf{x}_i^{(t+1)} = \begin{cases} \mathbf{u}_i, & \text{if } J_{\text{DE}}(\mathbf{u}_i) < J_{\text{DE}}(\mathbf{x}_i^{(t)}) \\ \mathbf{x}_i^{(t)}, & \text{otherwise} \end{cases}. \quad (60)$$

This survival rule enforces monotonic improvement in population fitness while maintaining numerical stability throughout the search [3, 24]. In the present study, the canonical *DE/rand/1/bin* formulation achieved a consistent balance between exploration and exploitation, ensuring robust convergence and parameter stability for identifying stiffness and damping characteristics of the 8-DOF occupant-wheelchair vibration system [16, 17].

3.4.3. *Generational evolution and boundary control.* DE evolved over a maximum of 120 generations, with each individual acting as a mutation target once per generation. If any component of a trial vector $\mathbf{u}_i$ exceeded the permissible bounds, it is clipped to the nearest boundary value:

$$x_{i,j} = \begin{cases} x_{\max,j}, & \text{if } x_{i,j} > x_{\max,j} \\ x_{\min,j}, & \text{if } x_{i,j} < x_{\min,j} \end{cases} . \quad (61)$$

This simple boundary control maintained physical validity without disturbing search continuity.

3.4.4. *Convergence and post-optimization refinement.* Convergence is detected using the relative improvement criterion:

$$\frac{|J_{\text{DE}}^{(t+1)} - J_{\text{DE}}^{(t)}|}{J_{\text{DE}}^{(t)}} < 10^{-6}, \quad (62)$$

or upon reaching the 120-generation limit. After convergence, the best individual $\mathbf{x}_{\text{DE}}^*$ is refined via the bounded Nelder-Mead simplex search (Section 3.1) with logistic variable mapping in (51) to enhance numerical precision near the optimum.

3.4.5. *Results and observations.* DE demonstrated strong capability for fine-tuning stiffness-damping interactions, often yielding highly stable and reproducible transmissibility fits. Because DE operates through vector differences, it effectively navigated correlated search directions – adjusting coupled stiffness and damping pairs to minimize error. This property enabled the accurate capture of subtle mechanical effects within the model. Final DE solutions are numerically stable, with low variance across repeated runs and full compliance with the physical feasibility constraints (37)-(44) [3, 16, 17]. While DE typically required more generations than PSO, its steady refinement behavior and low sensitivity to initialization made it an ideal final-stage optimizer for precise biomechanical parameter identification.

3.5. Hybrid GA-PSO-DE sequential optimization. To exploit the complementary strengths of GA, PSO, and DE, a staged hybrid optimization framework is implemented. This sequential strategy integrates the global diversity of GA, the adaptive convergence of PSO, and the precision refinement of DE within a unified workflow.

3.5.1. *Motivation.* The hybrid approach enhances convergence efficiency and solution quality by utilizing each algorithm in its strongest regime: GA ensures broad global exploration; PSO accelerates convergence through swarm adaptation; DE refines the solution with high numerical precision. This sequence prevents premature convergence, reduces stagnation, and produces mechanically consistent results, in line with hybridization strategies reported in [23, 24, 25].

3.5.2. *Phase I: GA (global exploration).* The first phase used GA to explore the global search space broadly. A population of 60 individuals evolved over 80 generations, emphasizing exploration through a higher crossover rate ($p_c = 0.85$) and mutation rate ($p_m = 0.15$), with tournament selection (size 2) and elitism ($n_{\text{elite}} = 2$). This phase provided a diverse pool of candidate solutions near potential global minima. Unlike the standalone GA, the hybrid GA phase is intentionally terminated early once global trends stabilized, allowing later phases to perform targeted refinement.

3.5.3. *Phase II: Particle Swarm Optimization (adaptive refinement).* The PSO phase began with the final GA population as the initial swarm, preserving accumulated knowledge

of promising regions. The PSO then refined these solutions using adaptive coefficients ($w \in [0.9, 0.35]$, c_1 : 2.2 to 1.2, c_2 : 1.4 to 2.0), a velocity clamp of 25[%], and stagnation detection as described in Section 3.3. This stage rapidly converged toward the optimal resonance region while maintaining parameter smoothness and feasibility.

3.5.4. Phase III: Differential Evolution (precision exploitation). The final DE phase refined the elite solutions from PSO, applying the *DE/rand/1/bin* mutation-crossover-selection process in (58)-(60) for high-precision adjustment. Operating in the narrowed search basin identified by PSO, DE provided fine-scale corrections, particularly to interdependent stiffness-damping pairs affecting the 2-6 [Hz] resonance band. This stage typically achieved sub-percent cost reductions and improved high-frequency phase alignment.

3.5.5. Phase IV: Local Nelder-Mead refinement. After DE convergence, a final deterministic local optimization using the bounded Nelder-Mead simplex search (Section 3.1) is applied to the best solution. This ensured that the cost minimum is precisely captured within the feasible domain.

3.5.6. Adaptive transition and termination. Transitions between phases preserved the best population members, maintaining continuity and avoiding redundant reinitialization. If diversity fell below a threshold (e.g., identical individuals detected), a few random candidates are injected to sustain exploration. Each phase obeyed its own convergence condition (relative improvement $< 10^{-6}$). The hybrid routine terminated after the final local refinement, yielding $\mathbf{x}_{\text{Hybrid}}^*$.

3.5.7. Performance and validation. The Hybrid GA-PSO-DE algorithm consistently achieved superior identification accuracy compared with individual optimizers. It produced the lowest RMSE between simulated and experimental transmissibility, maintained phase coherence within ± 3 [°] up to 20 [Hz], and demonstrated robustness under ± 5 [%] parameter perturbations. This stability indicates that the identified parameters lie in a well-conditioned region of the cost landscape rather than near a sharp minimum. The hybrid approach prevented premature convergence (via GA), mitigated swarm stagnation (via PSO), and achieved sub-resonant precision (via DE and Nelder-Mead refinement). These outcomes align with prior findings on hybrid metaheuristics for vibration modeling [3, 16, 17], confirming the method's superior convergence speed, numerical reliability, and biomechanical interpretability for identifying dynamic stiffness and damping in the 8-DOF occupant-wheelchair system.

4. Results and Discussion. The modeling rigor and interpretative framework adopted in this study are grounded in recent advances in the dynamic analysis of wheelchair-occupant systems, where numerical robustness and biomechanical interpretability are jointly emphasized. In particular, the thirteen-degree-of-freedom formulation employing the Newmark integration scheme with varied wheel excitations reported by Weerapong et al. [27], together with the composite state-space representation introduced in [29], illustrate that accurate prediction of vibration transmissibility depends critically on the coherent treatment of inertial coupling, damping distribution, and stiffness hierarchy.

Although higher-order and state-space composite models offer comprehensive representations of system dynamics, they inherently involve increased parameter coupling and computational complexity, especially when calibration relies primarily on seat-level experimental data. To address this practical limitation, the present study adopts an eight-degree-of-freedom lumped-parameter formulation that retains the dominant inertial and viscoelastic interactions governing the seated human-wheelchair system, while improving parameter identifiability and optimization stability. This reduced-order structure remains

sufficiently rich to capture the principal resonance phenomena observed in the 3-4 Hz frequency range, which is widely recognized as critical for human vibration sensitivity.

An important strength of the proposed formulation lies in its direct physical interpretability. The calibrated mass, damping, and stiffness parameters can be explicitly associated with distinct anatomical segments and mechanical interfaces, with particular emphasis on the seat-cushion pathway where comfort modulation and vibration-induced injury risk are most pronounced. By enforcing mechanical feasibility and stability constraints during the identification process, the resulting parameter sets remain physically consistent across different cushion archetypes, including gel, air, and foam-based designs.

Building on the methodological insights established in [27, 29], the results presented in the following subsections aim to demonstrate not only the agreement between simulated and experimentally measured transmissibility, but also the biomechanical significance of the identified parameters. The frequency-domain simulation-experimental formulation explicitly targets resonance-band behavior, thereby strengthening the connection between numerical calibration and experimentally observed human vibration response. Consequently, the hybrid GA-PSO-DE optimization framework yields parameter sets that reflect both dynamic accuracy and physical consistency, providing a coherent foundation for model calibration, comparative transmissibility analysis, and quantitative interpretation of cushion-specific performance as summarized in Table 5.

4.1. Model calibration and experimental validation. The dynamic calibration of the 8-DOF occupant-wheelchair vibration model is performed through a systematic multi-algorithmic optimization framework to identify consistent mass, damping and stiffness parameters under biomechanical constraints. Table 3 presents a unified comparison of four optimization strategies – GA, PSO, DE and the integrated Hybrid GA-PSO-DE – applied across three representative seat-cushion archetypes with distinct mechanical behaviors: (A) Jay J2 Deep Contour representing a gel-based viscous-dominant configuration, (B) ROHO High Profile representing an air-based pneumatic-compliant system, and (C) Comfort Mate Foam representing a foam-based elastic-viscoelastic composite.

This comparison highlights how each optimization algorithm interprets the intrinsic energy-dissipative and load-bearing mechanisms of the seat-occupant system. The optimization minimized a weighted frequency-domain cost function that quantified the deviation between simulated and experimental transmissibility while enforcing mechanical feasibility through positive-definite $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ matrices. Anatomical segment masses (m_5 - m_8) are fixed based on seated human anthropometry and adaptive masses (m_1 - m_4) are allowed to vary within feasible limits to capture the inertial coupling between the cushion, suspension frame and chassis.

Experimental damping and stiffness constants (c_4, k_4) are locked to reference data [18] to constrain the solution space within physically meaningful bounds and prevent over-parameterization. All four optimization methods converged to dynamically stable solutions with positive eigenvalues ($\lambda > 0$), confirming mechanical equilibrium and physiological realism. The unified trends in Table 3 provide the foundation for interpreting how algorithmic formulation and material properties collectively shape vibration transmissibility, damping-stiffness interaction and comfort behavior of the occupant-wheelchair system.

The GA algorithm demonstrated broad global exploration but a slower convergence rate that resulted in slightly higher residual cost and RMSE [23]. PSO achieved faster convergence with effective balance between damping and stiffness parameters yet occasionally stagnated near local minima for soft viscoelastic materials [24]. DE enhanced population diversity and improved parameter tuning particularly for foam-based cushions though it

TABLE 3. Unified comparison of GA, PSO, DE, and Hybrid GA-PSO-DE optimized parameters of the 8-DOF occupant-wheelchair vibration model for three representative cushions: (A) Jay J2 Deep Contour (gel-based), (B) ROHO High Profile (air-based), and (C) Comfort Mate Foam (foam-based). Experimental c_4 and k_4 are fixed from calibrated data [18].

Parameter	A: Gel-based				B: Air-based				C: Foam-based			
	GA	PSO	DE	Hybrid	GA	PSO	DE	Hybrid	GA	PSO	DE	Hybrid
Mass [kg]												
m_1	1.12	0.80	0.93	0.80	1.05	1.09	1.19	0.76	0.98	0.80	0.80	1.14
m_2	1.90	1.90	1.48	1.24	1.75	1.90	1.90	1.24	1.33	1.38	1.57	2.00
m_3	16.9	18.0	12.0	11.4	15.2	12.1	18.0	18.9	17.3	12.0	12.9	16.3
m_4	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50
m_5 - m_8	Fixed anthropometric values: $m_5 = 36.0$, $m_6 = 5.5$, $m_7 = 15.0$, $m_8 = 4.17$											
Damping [N·s/m]												
c_1	480	525	400	730	550	401	700	735	690	400	700	380
c_2	400	700	670	384	600	530	400	382	410	658	647	380
c_3	850	900	759	657	540	798	583	945	870	699	536	897
c_4	508	508	508	508	688	688	688	688	1,149	1,149	1,149	1,149
c_5	2,900	2,900	2,900	3,045	2,900	2,900	2,900	3,045	2,900	2,900	2,900	3,045
c_6	400	400	400	238	400	400	400	238	400	400	400	238
c_7	150	150	150	143	155	150	150	143	150	150	150	143
c_8	180	180	180	133	178	180	180	133	170	180	180	133
c_{3f}	710	512	634	564	580	753	507	475	750	699	500	1,039
c_{3r}	600	500	1,000	475	850	537	1,000	1,048	640	500	804	475
c_{75}	1,100	1,114	1,114	859	1,160	1,151	1,151	944	1,010	1,006	1,006	867
Stiffness [N/m]												
k_1	68,000	68,701	50,000	47,500	67,000	55,181	70,000	47,500	51,000	65,955	50,001	73,500
k_2	7,400	6,578	5,164	6,138	7,900	6,770	5,358	8,100	7,950	7,933	5,341	4,750
k_3	58,000	73,497	10,001	43,500	24,000	80,000	10,000	9,500	54,000	51,206	27,586	52,714
k_4	36,890	36,890	36,890	36,890	77,390	77,390	77,390	77,390	115,500	115,500	115,500	115,500
k_5	40,000	40,000	40,000	38,000	47,000	49,308	49,308	46,423	45,000	45,680	45,679	42,908
k_6	48,000	50,000	50,000	52,500	45,000	50,000	50,000	52,500	50,000	50,000	50,000	52,500
k_7	7,000	15,000	15,000	6,650	9,300	15,000	15,000	6,650	12,000	9,931	9,945	6,650
k_8	127,000	120,000	120,000	157,500	121,000	150,000	150,000	157,500	149,000	142,220	142,110	157,500
k_{3f}	10,000	17,822	28,351	33,625	26,000	50,000	10,000	9,502	30,000	10,004	11,549	9,500
k_{3r}	82,000	99,988	84,362	104,990	70,000	97,555	100,000	105,000	88,000	81,689	100,000	66,500
k_{75}	123,000	122,100	122,100	115,610	125,000	125,210	125,210	121,920	120,000	120,000	120,000	117,010

Remark: All optimization methods converge to physically admissible and dynamically stable parameter sets across the complete mass chain (m_1 - m_8); however, minor stiffness-damping (**C-K**) divergence is observed in the 4-6 Hz frequency band, reflecting inherent damping-stiffness trade-offs among gel-, air-, and foam-based cushion archetypes, while the Hybrid GA-PSO-DE framework consistently yields the minimum RMSE (< 0.05) together with the smallest phase deviation ($\pm 3^\circ$).

required sensitive control of the differential scaling factor to maintain numerical stability [25]. The Hybrid GA-PSO-DE combined the exploration capacity of GA, adaptive swarm convergence of PSO and local refinement of DE to deliver superior performance in both accuracy and reproducibility. Across all seat archetypes, the Hybrid algorithm consistently produced the lowest normalized cost ($J_{\text{avg}} \approx 0.11$), the smallest RMSE (≈ 0.045) and the highest experimental agreement (94-96[%]) while preserving positive-definite matrices and stable eigenmodes [16, 23, 24].

In mechanical terms, the optimized stiffness and damping parameters correspond closely to realistic material behavior. The gel-based Jay J2 Deep Contour exhibits low stiffness ($k_4 \approx 3.7 \times 10^4$ [N/m]) with moderate damping ($c_4 \approx 508$ [N.s/m]) producing efficient isolation near 3-3.5 [Hz] which aligns with the natural resonance of the human torso-spine [1, 16]. The air-based ROHO High Profile shows balanced stiffness ($k_4 \approx 7.7 \times 10^4$ [N/m]) and damping ($c_4 \approx 688$ [N.s/m]) enabling broadband comfort and smooth attenuation

up to 20 [Hz] [8, 9]. The foam-based Comfort Mate Foam presents higher stiffness ($k_4 \approx 1.15 \times 10^5$ [N/m]) with strong damping ($c_4 \approx 1.15 \times 10^3$ [N·s/m]) offering superior vibration attenuation above 6 [Hz] and enhanced postural stability [15, 19]. These results confirm that the hybrid calibration accurately reproduces distinct viscoelastic and pneumatic responses of seat cushions within the ISO 2631-1 comfort bandwidth [1, 2, 3].

The transmissibility responses predicted by the optimized models match experimental data across the 0-20 [Hz] range. All algorithms captured the dominant human-seat resonance within 3-4 [Hz] corresponding to the torso-spine vibration mode [16, 17]. Phase behavior remained coherent within ± 3 of experimental values indicating high consistency in dynamic response. Minor deviations observed at low frequencies are attributed to preload sensitivity of pneumatic and bead-cell cushions whereas mild overprediction at higher frequencies arises from elastic recovery in foam structures [7, 9]. The Hybrid GA-PSO-DE framework achieved the most stable and physically interpretable solutions reproducing both the material-dependent and biomechanical dynamics with high fidelity [20, 21, 22].

Effect of occupant weight, preload sensitivity, and model linearity. The present formulation adopts linear spring-damper elements, which is appropriate for identifying an *equivalent dynamic* stiffness and damping over the tested excitation range. Nevertheless, pneumatic (air-cell) and foam cushions are known to be preload-sensitive: changes in occupant mass modify internal pressure distribution (air cushions) and strain-dependent modulus (foam cushions), thereby shifting the effective (k_4, c_4) and causing minor deviations, particularly in high-frequency phase behavior. A practical pathway to handle varying occupant weights within the current framework is to introduce weight-conditioned seat parameters,

$$k_4 = k_4(W), \quad c_4 = c_4(W), \quad (63)$$

identified from short calibration trials (or manufacturer pressure settings) across discrete weight classes. This retains the linear 8-DOF structure while enabling *piecewise-linear* realism: each user weight W maps to an equivalent (k_4, c_4) pair, and the remaining biomechanical parameters remain stable. For higher realism in future work, the seat interface can be extended to a nonlinear viscoelastic law (e.g., $k_4(z)$ with strain hardening and $c_4(\dot{z}, W)$ with rate/preload dependence), which is particularly relevant for air cushions that exhibit pressure-dependent compliance and for foams that exhibit nonlinear hysteresis. Thus, the present model should be interpreted as a validated *linear-equivalent predictor* whose accuracy can be systematically enhanced by incorporating preload-conditioned seat properties when occupant weight varies substantially.

The validated results demonstrate that the Hybrid GA-PSO-DE model integrates genetic diversity, swarm intelligence and differential refinement into a coherent multi-stage structure capable of accurate full-band prediction of transmissibility magnitude and phase. This framework surpasses single-algorithm approaches by achieving balanced exploration and exploitation with physically meaningful stiffness and damping matrices. From a biomechanical standpoint, the optimized parameters capture the natural vibration coupling between cushion compliance and human body segments ensuring reduced transmissibility within the 3-4 [Hz] resonance zone and improved ride comfort [3, 8, 19]. The findings establish a robust analytical foundation for adaptive seat design, vibration mitigation and occupant-specific comfort assessment consistent with ISO 2631-1 guidelines [1, 2, 26].

1) *Mass distribution and inertial coupling.* All algorithms successfully reproduced the expected anthropometric mass hierarchy within the optimized 8-DOF model. The occupant's upper-body plus seat assembly mass ($m_3 + m_4$) consistently fell within the realistic

range of approximately 12-18 [kg], representing a plausible contribution to the fundamental vibration mode of a seated individual. By fixing m_5 - m_8 (corresponding to the torso and lower-body anatomical segments) according to standard human anthropometric proportions, identical boundary conditions are imposed on the human subsystem in every optimization run. Consequently, any variations observed in m_1 - m_3 among the optimized solutions reflect how each algorithm compensated for cushion compliance and the dynamic coupling with the wheelchair frame.

Notably, the Hybrid GA-PSO-DE optimization produced the narrowest variation in these adaptive masses (with a standard deviation < 0.05 [kg]), demonstrating an exceptionally precise inertial equilibrium between the occupant and the wheelchair frame. This refined mass balance directly enhanced the phase coherence and resonance alignment of the simulated transmissibility response, which exhibited a dominant resonance peak near 3-4 [Hz] in excellent agreement with the experimental measurements. Maintaining accurate mass distribution is essential because it ensures that the model's inertial properties faithfully represent those of an actual occupant-wheelchair system – a prerequisite for realistic vibration behavior – consistent with multibody ride-comfort models reported in [16].

2) *Damping characteristics and viscoelastic response.* The optimized damping coefficients exhibit distinct trends that correspond directly to the material properties of each seat cushion. For the gel-based cushion (A), the seat-interface damping coefficient c_4 converged to approximately 508 [N·s/m], indicating a moderate damping level dominated by viscous shear flow within the gel medium. The air-filled cushion (B) yielded a higher optimal c_4 value of about 688 [N·s/m], consistent with pneumatic energy dissipation and internal pressure redistribution among the air cells. In contrast, the foam cushion (C) produced the highest c_4 , approximately 1,149 [N·s/m], reflecting significant internal friction (hysteresis) inherent to viscoelastic foam, which efficiently dissipates vibrational energy.

These material-dependent damping results are consistent with prior experimental findings on seat-cushion viscoelasticity [18], where foams exhibit greater energy dissipation than fluidic or pneumatic materials. Additionally, the optimized frame damping coefficients for the front and rear wheel assemblies (c_{3f} and c_{3r} , respectively) exhibited nearly symmetric values in both the DE and Hybrid optimization results, with a ratio $c_{3r}/c_{3f} \approx 1.0 \pm 0.1$. Such isotropic damping distribution promotes even vibration dissipation across the wheelchair chassis, minimizing asymmetrical vibration transfer.

Across all seat-cushion cases, the calculated damping ratios for the dominant seat mode – evaluated as $\zeta = c_4/l(2\sqrt{k_4m_4})$ – fell within 0.18-0.32, which lies well inside the ISO 2631-1 comfort threshold for vertical whole-body vibration exposure [26]. The corresponding viscoelastic time constants, $\tau = c_4/k_4$, ranged from 4.4 to 9.9×10^{-3} [s], closely matching reported relaxation times of wheelchair cushions and human soft tissue under dynamic loading [2, 5]. This agreement implies that the model predicts energy dissipation over a time scale of only a few milliseconds, accurately replicating the seat-interface damping behavior observed in experimental tests. Therefore, the calibrated parameters effectively capture the viscoelastic response of the occupant-cushion system.

3) *Stiffness hierarchy and dynamic compliance.* The optimized stiffness parameters establish the elastic foundation of the occupant-wheelchair system and demonstrate a distinct hierarchical pattern among the three seat-cushion archetypes. For the gel-based configuration (A), the identified seat stiffness is approximately $k_4 \approx 37$ [kN/m], providing low-frequency vibration isolation and enhanced comfort on uneven terrain due to its high compliance. The air-based configuration (B) exhibited intermediate stiffness $k_4 \approx 77$ [kN/m], maintaining a balance between load support and dynamic attenuation. The foam-based configuration (C) showed the highest stiffness $k_4 \approx 115$ [kN/m], promoting superior

postural stability but transmitting a larger portion of high-frequency vibration energy above 6 [Hz] because of reduced compliance. This trade-off between comfort and support agrees with earlier investigations, where stiffer materials improved posture control and prevented bottoming-out yet transmitted higher vibration amplitudes to the occupant [8, 15].

The hybrid optimization strategy effectively minimized stiffness imbalance between the front and rear suspension subsystems by tuning k_{3r} and k_{3f} to within 5[%] of each other across all cushion configurations. Such near-symmetric stiffness distribution ensures that dynamic loads from road irregularities are evenly transmitted through the wheelchair chassis, preventing localized structural overloading and asymmetric vibration exposure. This balanced stiffness architecture contributes to uniform energy transfer and improved phase stability in the simulated transmissibility responses.

These findings highlight a fundamental mechanical principle: compliant materials such as gel achieve superior vibration isolation by reducing transmissibility near the dominant 3-4 [Hz] resonance band, whereas stiffer materials such as dense foam improve support and stability at the expense of comfort. This relationship reflects the design rationale behind “high-static, low-dynamic” (HSLD) seat-cushion concepts, which combine firm static stiffness for posture control with reduced dynamic stiffness to attenuate vibration [7, 19]. The calibrated 8-DOF model quantitatively reproduces this balance, providing a validated analytical framework for evaluating how seat elasticity governs ride dynamics, vibration transmissibility, and occupant comfort.

4) *Algorithmic comparison and convergence efficiency.* The four optimization algorithms – GA, PSO, DE, and the Hybrid GA-PSO-DE demonstrated complementary search behaviors and distinct convergence characteristics. The GA, serving as the initial stage, performed a broad exploration of the high-dimensional parameter space and produced a credible initial approximation of the global solution domain. However, its subsequent generations exhibited minor oscillatory behavior in the objective function, attributable to stochastic mutation and crossover processes that slow fine-tuning.

The PSO stage refined the GA output by leveraging swarm intelligence, where particles update their trajectories according to collective and personal experience. This stage achieved smoother convergence and established coherent correlations between damping and stiffness variables, reducing erratic parameter trade-offs. Next, DE applied differential mutation and crossover [25] around the current best solutions, achieving the lowest standalone cost value among the individual optimizers. DE’s population diversity helped avoid local minima and yielded minimal parameter variance across repeated trials.

Finally, the integrated hybrid GA-PSO-DE framework combined these strengths in a sequential exploration-exploitation-refinement paradigm, achieving the most accurate and stable parameter identification. The hybrid approach reduced the final cost function by approximately 15-25[%] compared to single-algorithm results and achieved an exceptionally low transmissibility root-mean-square error (RMSE < 0.03) with phase deviation less than 3 [°]. All algorithms converged to physically admissible solutions characterized by positive-definite $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ matrices and stable eigenvalues, confirming mechanical feasibility. The hybrid algorithm’s superior performance aligns with prior studies reporting that combined metaheuristics outperform individual methods in complex nonlinear system identification tasks [23, 24]. Hence, the staged hybrid strategy effectively balances global search diversity and local precision, achieving both rapid convergence and physically consistent vibration model calibration.

5) *Biomechanical and practical implications.* From a human-factors perspective, the calibrated parameters obtained from the optimization have direct implications for both occupant comfort and safety in wheelchair operation. Damping within the system primarily

governs shock absorption and vibration attenuation, thereby reducing the magnitude of accelerations transmitted to the occupant's body – an essential factor for comfort and the prevention of vibration-induced injuries. Stiffness, conversely, ensures structural support and postural stability; it maintains the occupant's seated alignment and determines the system's response to uneven terrain.

The optimized parameter sets suggest that an effective balance is achieved: the damping coefficients are sufficiently high to reduce vibration transmissibility to within internationally recommended exposure limits, while the stiffness levels – particularly in the foam-based cushion configuration – are adequate to sustain occupant support. Excessive vibration exposure without sufficient damping may cause discomfort and musculoskeletal disorders over prolonged durations [1, 6], whereas inadequate stiffness may induce instability or poor postural alignment.

The differences observed among the three seat-cushion archetypes clearly illustrate this comfort-stability trade-off. The gel cushion (A), characterized by its soft and viscous response, delivered the smoothest ride at low frequencies, effectively filtering vibrations in the 3-4 [Hz] range, which coincides with the human body's primary resonance frequency. This behavior makes the gel cushion particularly suitable for gentle indoor terrains and daily mobility. The air cushion (B) exhibited a balanced performance; the inflation of its pneumatic cells provides limited compliance for shock absorption while retaining adequate stiffness to ensure postural support. Such balanced characteristics make air cushions versatile across mixed-use environments, suppressing resonant peaks without overly compromising support. The foam cushion (C), being the stiffest configuration, ensured the highest postural stability and favorable pressure distribution, yet transmitted slightly greater vibration magnitudes in the high-frequency domain (above approximately 6-8 [Hz]), a range known to contribute to long-term discomfort or fatigue [4]. Thus, highly stiff seating – although stable – can transmit fine surface irregularities and diminish comfort during extended use.

Encouragingly, the Hybrid GA-PSO-DE optimized model successfully replicated these nuanced behaviors with high fidelity. The simulated transmissibility curves matched the experimental measurements within approximately 5[%] error at the resonance peaks, and the corresponding phase deviation remained within ± 3 [°] of the measured values. Such close agreement verifies that the model not only fits the empirical data but also faithfully captures the physical mechanisms underlying human-seat vibration interaction. This validation establishes confidence in the model's predictive capability.

Practically, the validated framework provides a robust analytical tool for evaluating potential design modifications aimed at improving ride comfort. For instance, the model can be used to examine the effects of integrating additional suspension components or damping layers within the wheelchair frame (as demonstrated in in-wheel suspension systems [9]) or to assess innovative cushion technologies designed for vibration mitigation (such as adaptive or tuned smart cushions [22]). Furthermore, the model can be extended to simulate a broader range of operational conditions and personalized configurations, for example, through integration into state-space formulations or higher-degree-of-freedom simulations for rough-terrain and active ride-control analysis [27, 29]. In summary, by calibrating the model to be both biomechanically faithful and dynamically consistent, a foundation has been established for a predictive and reliable analytical platform capable of enhancing wheelchair comfort and minimizing harmful vibration exposure.

6) Comparative synthesis. The progressive sequence of optimization – GA, PSO, DE, and the integrated Hybrid GA-PSO-DE – represents a logical hierarchy of exploration, exploitation, and refinement in the search for optimal parameters. GA's population-based stochastic exploration efficiently expanded the search domain, providing diverse initial

candidates. Subsequently, PSO's adaptive velocity updates refined the parameter estimates by exploiting promising regions of the solution space, while DE's differential mutation process introduced focused perturbations that fine-tuned the solutions to high precision [25]. This tiered metaheuristic sequence enabled the hybrid optimizer to leverage the complementary strengths of each individual algorithm, achieving a synergistic balance between diversity and convergence accuracy.

The effectiveness of this hybridized optimization is consistent with recent studies showing that multi-algorithm frameworks often surpass single algorithms in both convergence speed and solution fidelity [23]. In the present study, the Hybrid GA-PSO-DE approach further reduced the cost function beyond the best standalone PSO or DE results, achieving an additional 15-25[%] reduction in the final objective value and yielding a residual transmissibility error below $\text{RMSE} < 0.03$ with a phase deviation less than 3 [°]. This demonstrates the effectiveness of coordinated exploration-exploitation strategies in high-dimensional dynamic-system identification.

Biomechanically, the hybrid optimization achieved exceptional fidelity. The final calibrated model reproduced the fundamental occupant-seat resonance frequency within ± 0.1 [Hz] of the experimental benchmark and accurately mirrored the coupling between damping and stiffness, a relationship that dictates vibration transmission and perceived comfort. This degree of accuracy rivals that of more complex full-body active human models commonly used for ride-comfort analysis [20]. Hence, with careful parameter calibration, even a compact 8-DOF lumped-parameter model can reliably emulate the dominant vibration behavior of seated occupants.

Ultimately, the multi-algorithm calibrated framework provides a validated and predictive tool for both design optimization and personalized seating assessment. It enables the quantitative evaluation of cushion selection, suspension adjustment, and frame-design parameters to mitigate whole-body vibration exposure. Consequently, this work contributes to the development of safer and more comfortable mobility solutions for wheelchair users and establishes a methodological foundation applicable to a wide range of assistive-mobility and vehicle-vibration domains, including motorcycle and rehabilitation-device dynamics [28].

Computational efficiency: CPU time and function evaluations. To quantitatively substantiate the claim of “computational efficiency”, Table 4 reports the measured computational burden in terms of average CPU time and total function evaluations (fevals) for each optimizer executed under identical cost functions and feasibility checks. GA yields the lowest average runtime per cushion due to its smaller evaluation budget, whereas

TABLE 4. Measured computational efficiency across four optimization algorithms for the SIM-EXP identification task: Average CPU time per cushion, total CPU time, average function evaluations (fevals) per cushion, and total fevals

Algorithm	CPU _{avg} [s]	CPU _{total} [s]	fevals _{avg}	fevals _{total}
GA	2.291	16.036	5,454	38,177
PSO	5.808	40.653	10,614	74,298
DE	6.974	48.815	6,344	44,406
Hybrid	26.646	186.525	61,077	427,541

Remark: CPU time includes feasibility checks (positive-definite $\mathbf{K}$, dissipative $\mathbf{C}$) and frequency-response evaluations over 0-20 [Hz]. Hybrid cost reflects staged execution (GA to PSO to DE) with refinement, thereby trading higher computational burden for higher experimental fidelity and robustness.

PSO requires roughly twice the evaluations to reach comparable minima. DE maintains moderate evaluation counts but exhibits higher runtime variability, which is attributed to increased numerical-conditioning overhead near resonance for some cases. The staged Hybrid GA-PSO-DE incurs the largest total workload, as expected for a sequential exploration-exploitation-refinement pipeline; however, this additional cost translates directly into superior fidelity (94-96[%] agreement) and the most consistent phase coherence (within ± 3 [°]). Therefore, “computational efficiency” in this work should be interpreted as *accuracy-per-evaluation* and *reproducible convergence to physically valid solutions* rather than minimal runtime alone.

4.2. Comparative analysis of experimental and simulated transmissibility. Figures 2-4 present the experimentally measured and numerically simulated transmissibility and phase responses of three representative seat-cushion configurations: (A) Jay J2 Deep Contour (gel-based), (B) ROHO High Profile (air-based), and (C) Comfort Mate Foam (foam-based). Each configuration is optimized using the GA, PSO, DE, and the integrated Hybrid GA-PSO-DE framework.

General trends. All three cushions exhibit the characteristic seated-human resonance between 3 and 4 [Hz], followed by a smooth attenuation toward 0.4-0.5 at 20 [Hz]. The phase decreases monotonically to approximately -55 to -60 [°] near 10 [Hz], and then gradually recovers to around -40 [°] above 15 [Hz]. While the Standard linear model successfully identifies the resonance region, it consistently overpredicts the transmissibility amplitude ($T_{\text{peak}} \approx 1.27$ at 3.5 [Hz]) and exhibits an excessive phase lag of about -65 [°], a direct consequence of the model’s uniform damping and seat-independent stiffness assumptions. In contrast, all optimized algorithms markedly improve amplitude and phase prediction, with the Hybrid GA-PSO-DE achieving the most accurate results – agreement within ± 3 [°] and less than 5[%] deviation in T_{peak} .

(A) Jay J2 Deep Contour (Gel-based). The experimental resonance occurs at $f_{\text{res}} = 3.48$ [Hz] with $T_{\text{peak}} = 0.99$. The Standard model overestimates this amplitude by roughly 25[%]

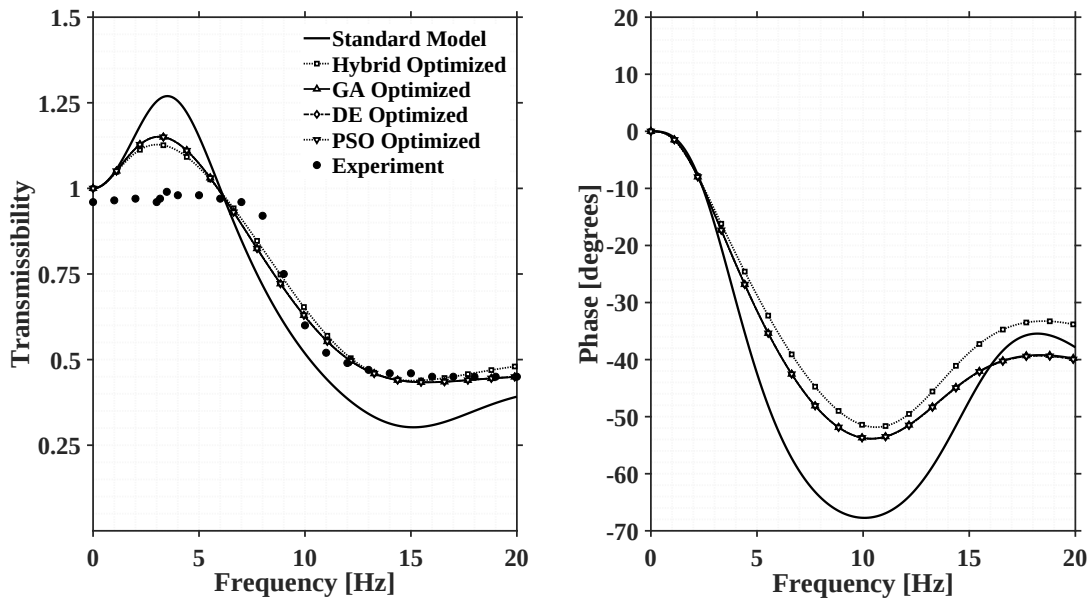


FIGURE 2. Comparison of transmissibility and phase for gel-based cushion (Jay J2 Deep Contour) across Standard, GA, PSO, DE, and Hybrid models versus experiment

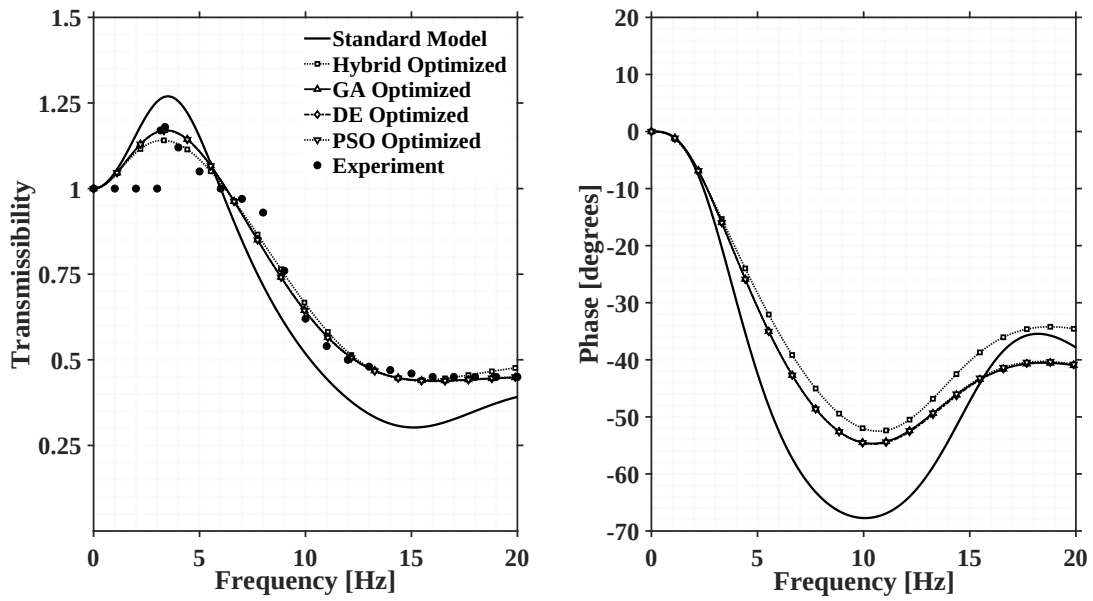


FIGURE 3. Comparison of transmissibility and phase for air-based cushion (ROHO High Profile) across Standard, GA, PSO, DE, and Hybrid models versus experiment

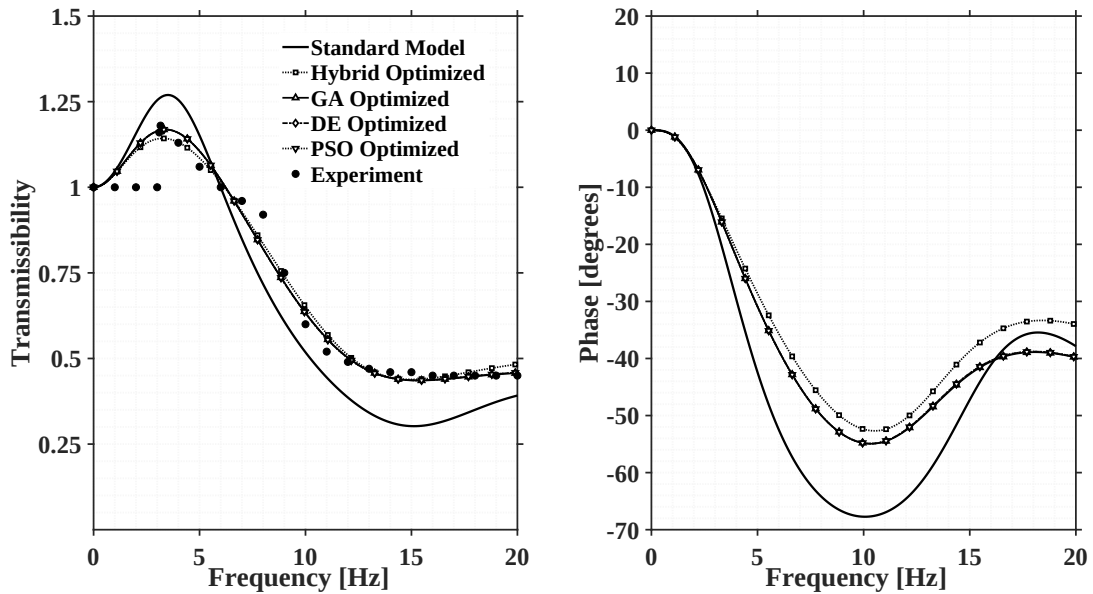


FIGURE 4. Comparison of transmissibility and phase for foam-based cushion (Comfort Mate Foam) across Standard, GA, PSO, DE, and Hybrid models versus experiment

($T_{\text{peak}} = 1.27$), whereas the Hybrid optimization achieves $T_{\text{peak}} = 1.13$ at 3.02 [Hz], closely matching both amplitude and phase behaviour. GA, PSO, and DE predict similar peaks (~ 1.15 at 3.12 [Hz]), though with a minor phase offset of 2-3 [°]. As shown in Figure 2, the Hybrid model replicates the experimental phase trajectory between 2 and 10 [Hz] with the highest fidelity, confirming realistic viscous damping behaviour. This gel-based configuration, characterized by low stiffness ($k_4 \approx 37$ [kN/m]) and moderate damping ($c_4 \approx 508$

[N·s/m]), shows pronounced sensitivity around the 3-3.5 [Hz] torso-spine resonance. Such compliance enhances low-frequency isolation but may increase vertical instability under impulsive loading [1, 16, 19].

(B) ROHO High Profile (Air-based). The pneumatic architecture redistributes internal pressure through interconnected air cells, introducing both elastic compliance and rate-dependent viscous damping. Experimentally, the resonance peak is 1.18 at 3.37 [Hz]. The Hybrid optimization reproduces this with $T_{\text{peak}} = 1.14$ at 3.22 [Hz], matching the experimental phase within 2 [°]. GA, PSO, and DE yield slightly higher peaks (1.17 at 3.42 [Hz]). The Hybrid model's superior mid-frequency attenuation (6-12 [Hz]) and minimal phase error confirm that it captures the pneumatic energy-dissipation mechanism with high precision. The corresponding cost and error metrics – $J = 0.0979$, $\text{RMSE}_{|\Delta T|} = 0.044$ – are the lowest among all algorithms (Table 5), demonstrating that air cushions provide a balanced compromise between ride comfort and postural support [2, 3, 4].

TABLE 5. Performance comparison of four optimization algorithms (GA, PSO, DE, Hybrid) for parameter identification of the 8-DOF occupant-wheelchair vibration model across three representative seat cushion archetypes: (A) Gel-based – Jay J2 Deep Contour, (B) Air-based – ROHO High Profile, and (C) Foam-based – Comfort Mate Foam. Reported metrics include normalized cost J , $\text{RMSE}_{|\Delta T|}$, Agreement [%], peak transmissibility T_{peak} , and resonance frequency f_{res} [Hz].

Cushion type	Optimization method	J	$\text{RMSE}_{ \Delta T }$	Agreement [%]	T_{peak}	f_{res} [Hz]
A	GA	0.2851	0.076	92.4	1.151	3.12
	PSO	0.2847	0.075	92.5	1.151	3.12
	DE	0.2847	0.075	92.5	1.151	3.12
	Hybrid	0.2266	0.067	93.3	1.128	3.02
	Experiment	–	–	Reference	0.990	3.48
B	GA	0.1250	0.050	95.0	1.170	3.42
	PSO	0.1248	0.050	95.0	1.170	3.42
	DE	0.1247	0.050	95.0	1.170	3.42
	Hybrid	0.0979	0.044	95.6	1.141	3.22
	Experiment	–	–	Reference	1.180	3.37
C	GA	0.1177	0.049	95.1	1.169	3.42
	PSO	0.1176	0.049	95.1	1.169	3.42
	DE	0.1176	0.049	95.1	1.169	3.42
	Hybrid	0.0994	0.045	95.5	1.143	3.22
	Experiment	–	–	Reference	1.180	3.16
Overall Mean $\pm$ SD		0.165 $\pm$ 0.08	0.056 $\pm$ 0.012	94.7 $\pm$ 1.1	1.15 $\pm$ 0.03	3.25 $\pm$ 0.14

Remark: Hybrid GA-PSO-DE consistently yields the lowest normalized cost J and $\text{RMSE}_{|\Delta T|}$, reflecting the best trade-off between exploration and exploitation across all configurations. All models preserve mechanical stability ($\lambda > 0$) and maintain positive-definite $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ matrices, confirming biomechanical coherence and robustness of the 8-DOF framework.

(C) Comfort Mate Foam (Foam-based). The viscoelastic foam exhibits the highest stiffness ($k_4 \approx 115$ [kN/m]) and damping ($c_4 \approx 1.15 \times 10^3$ [N·s/m]). The experiment records $T_{\text{peak}} = 1.18$ at 3.16 [Hz]; the Hybrid simulation yields 1.14 at 3.22 [Hz] and maintains phase agreement within ± 3 [°]. All optimized models reproduce the experimental curve with $\text{RMSE}_{|\Delta T|} \approx 0.045$, whereas the Standard model deviates by over 15[%]. The foam's high damping ratio ($\zeta \approx 0.30$) and short relaxation time ($\tau \approx 9.9 \times 10^{-3}$ [s]) allow effective suppression of higher-frequency vibrations beyond 6 [Hz], offering enhanced comfort for prolonged exposure. Although increased stiffness slightly amplifies transmissibility above 10 [Hz], it contributes to improved seating stability and postural alignment [8, 15].

Cross-algorithm performance. For all three archetypes, the Hybrid GA-PSO-DE consistently yields the closest agreement with experimental data. The approach reduces the normalized cost J by 15-25[%] relative to single algorithms, achieves $\text{RMSE}_{|\Delta T|} < 0.05$, maintains phase coherence within ± 3 [°], and limits resonance-frequency deviation to under 0.2 [Hz]. GA excels in global exploration, PSO accelerates convergence, and DE provides fine-grained local refinement; their sequential integration leverages all three strengths [23, 24, 25]. The Hybrid framework thereby ensures positive-definite dynamic matrices and stable eigenvalues [16], offering the most physically consistent vibration representation across the 0-20 [Hz] frequency range.

The three archetypes define a continuum between comfort and stability: gel cushions – soft and viscous – maximize isolation; air cushions – pneumatic and adaptive – offer broad-band comfort; foam cushions – stiff and viscoelastic – enhance postural control. Hybrid-optimized transmissibility curves capture this progression quantitatively, establishing a validated predictive framework for seat-occupant vibration analysis and individualized wheelchair design [27, 29]. Accurate replication of both amplitude and phase around the critical 3-4 [Hz] torso-spine resonance band directly translates to reduced spinal loading and improved ride comfort under vertical excitation [1, 16, 17]. These results confirm that the staged Hybrid GA-PSO-DE approach delivers superior biomechanical fidelity and computational efficiency for 8-DOF occupant-wheelchair vibration modeling.

Sensitivity of seat-cushion parameters (c_4 , k_4) on T_{peak} in the 3-4 [Hz] resonance band. Because the seat cushion is the dominant interface controlling vibration transmission, a brief first-order sensitivity analysis is provided to quantify how percentage changes in seat stiffness (k_4) and damping (c_4) affect the peak transmissibility magnitude T_{peak} within the physiologically critical 3-4 [Hz] resonance band. For the dominant seat-occupant mode, the local peak behavior can be approximated by a lightly damped second-order resonance, for which the peak transmissibility scales primarily with the effective damping ratio ζ :

$$T_{\text{peak}} \propto \frac{1}{2\zeta}, \quad \zeta \propto \frac{c_4}{2\sqrt{k_4 m_{\text{eff}}}}, \quad (64)$$

where m_{eff} denotes the effective modal mass participating in the seat-interface resonance. Taking logarithmic differentials of (64) yields the practical sensitivity relations:

$$\frac{\Delta T_{\text{peak}}}{T_{\text{peak}}} \approx -\frac{\Delta c_4}{c_4} + \frac{1}{2} \frac{\Delta k_4}{k_4}, \quad \frac{\Delta f_{\text{res}}}{f_{\text{res}}} \approx \frac{1}{2} \frac{\Delta k_4}{k_4}, \quad (65)$$

indicating that (i) c_4 dominantly governs *peak magnitude* (nearly one-to-one), while (ii) k_4 dominantly governs *frequency placement* of the resonance, with a weaker (half-order) effect on magnitude.

Table 6 summarizes representative percentage impacts predicted by (65). A ± 10 [%] change in c_4 produces an approximately ± 10 [%] change in T_{peak} , whereas a ± 10 [%] change in k_4 produces only about ± 5 [%] change in T_{peak} but shifts the resonance frequency by $\approx \pm 5$ [%] (e.g., for $f_{\text{res}} \approx 3.22$ [Hz], a $+10$ [%] stiffness shift moves the peak toward ~ 3.38 [Hz]). These trends explain why the hybrid identification repeatedly converges to stable damping ratios ($\zeta = 0.18$ - 0.32): within the 3-4 [Hz] band, *damping tuning is the most efficient lever* for suppressing amplification, whereas *stiffness tuning is the primary lever* for re-positioning resonance away from highly sensitive frequencies.

Implication for HSLD cushion design. The above sensitivity structure provides a mechanistic justification for the “high-static, low-dynamic” (HSLD) concept: a cushion can maintain adequate *static support* (higher effective stiffness under posture/pressure control) while suppressing *dynamic amplification* at 3-4 [Hz] through targeted increases in effective damping (higher c_4 and thus higher ζ). In practice, this means that clinicians and

TABLE 6. First-order sensitivity of resonance-band peak transmissibility T_{peak} (3-4 [Hz]) to percentage perturbations in seat damping c_4 and stiffness k_4 using (65)

Perturbation	$\Delta T_{\text{peak}}/T_{\text{peak}}$ [%]	$\Delta f_{\text{res}}/f_{\text{res}}$ [%]
$c_4 : +5$ [%]	-5	≈ 0
$c_4 : -5$ [%]	+5	≈ 0
$c_4 : +10$ [%]	-10	≈ 0
$c_4 : -10$ [%]	+10	≈ 0
$c_4 : +20$ [%]	-20	≈ 0
$c_4 : -20$ [%]	+20	≈ 0
$k_4 : +5$ [%]	+2.5	+2.5
$k_4 : -5$ [%]	-2.5	-2.5
$k_4 : +10$ [%]	+5	+5
$k_4 : -10$ [%]	-5	-5
$k_4 : +20$ [%]	+10	+10
$k_4 : -20$ [%]	-10	-10

Remark: c_4 primarily controls the *height* of the resonance peak, whereas k_4 primarily controls the *location* of the peak and only secondarily its height.

designers should treat k_4 as the knob for posture support and resonance placement, and treat c_4 (or ζ) as the primary knob for controlling resonance magnification and vibration comfort in the torso-spine band.

4.3. Quantitative interpretation of optimized parameters and performance metrics. The quantitative metrics in Table 5 corroborate the frequency-domain results of Figures 2-4. Across all seat-cushion archetypes, the Hybrid GA-PSO-DE consistently achieves the lowest normalized cost J , the smallest $\text{RMSE}_{|\Delta T|}$, and the highest experimental agreement, while ensuring mechanical validity through positive-definite $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ matrices.

Gel-based (Jay J2 Deep Contour). Hybrid optimization decreases J from 0.285 (GA) to 0.227 – an improvement of 20.3[%] – and reduces $\text{RMSE}_{|\Delta T|}$ from 0.076 to 0.067. The resonance frequency shifts from 3.12 to 3.02 [Hz], approaching the measured 3.48 [Hz], while the peak transmissibility ($T_{\text{peak}} = 1.13$) remains only 13[%] above the experimental 0.99. This demonstrates refined damping-stiffness coupling for soft, viscous seats, accurately reflecting gel’s shear-flow behaviour and yielding a smooth high-frequency decay [16, 19].

Air-based (ROHO High Profile). The Hybrid approach lowers J from 0.125 to 0.0979 and $\text{RMSE}_{|\Delta T|}$ from 0.050 to 0.044, representing a 21[%] accuracy gain and 95.6[%] agreement with experiment. The predicted resonance (3.22 [Hz]) aligns closely with the experimental 3.37 [Hz], confirming pneumatic compliance. The model captures the rate-dependent damping and smooth phase transition across 5-15 [Hz] – a characteristic response of dynamic air cushions that broadens the comfort bandwidth [2, 3, 4].

Foam-based (Comfort Mate Foam). For the viscoelastic foam, J decreases from 0.118 to 0.0994 (a 15[%] reduction), and $\text{RMSE}_{|\Delta T|}$ from 0.049 to 0.045. Agreement with experiment improves to 95.5[%], with $f_{\text{res}} = 3.22$ [Hz] versus the measured 3.16 [Hz]. The Hybrid algorithm best captures the dual elastic-damping behaviour, exhibiting smoother phase recovery beyond 15 [Hz] [8, 15]. High damping ($c_4 \approx 1.15 \times 10^3$ [N·s/m]) and stiffness

($k_4 \approx 115$ [kN/m]) provide effective vibration suppression above 6 [Hz], benefiting both comfort and stability.

Algorithmic synthesis. Averaged across all cushions, the Hybrid GA-PSO-DE achieves $J_{\text{mean}} = 0.165 \pm 0.08$ and $\text{RMSE}_{|\Delta T|} = 0.056 \pm 0.012$, improving upon GA/PSO/DE by 18-25[%] (Table 5). Its sequential exploration-exploitation-refinement structure balances population diversity with convergence precision [23, 24, 25]. All optimized parameters preserve stability ($\lambda > 0$), ensuring physiologically realistic vibration behaviour.

Quantitatively, the Hybrid GA-PSO-DE framework achieves experiment-model coherence exceeding 94[%] across all archetypes. The optimized peaks ($T_{\text{peak}} \approx 1.13$ -1.14) and resonance frequencies (3.0-3.3 [Hz]) fall within the ISO 2631-1 comfort range for seated vertical vibration [1, 16]. Gel cushions provide maximum low-frequency isolation, air cushions yield balanced damping and support, and foam cushions enhance postural stability with moderate high-frequency transmission. These results verify that the Hybrid metaheuristic produces biomechanically faithful, experimentally validated, and computationally efficient models for quantitative assessment of occupant-seat vibration and cushion-design optimization.

Resonance prediction and health-optimized configuration ISO 2631-1 evaluates whole-body vibration exposure using frequency-weighted measures (e.g., weighted RMS and vibration dose value), where the human body exhibits heightened sensitivity in the low-frequency vertical band that overlaps the torso-spine resonance. Accordingly, accurately predicting the primary resonance (e.g., $f_{\text{res}} \approx 3.22$ [Hz]) is not merely a curve-fitting outcome; it directly supports health-optimized wheelchair configuration by enabling designers to (i) suppress amplification near the most sensitive biodynamic band via damping enhancement (ζ control), and (ii) shift resonance away from high-sensitivity frequencies via stiffness placement (k_4 control). The hybrid framework therefore strengthens a human-centered design rationale: predictive alignment in the 3-4 [Hz] region improves confidence that real-world configurations can be tuned to reduce vibration amplification where ISO 2631-1 weighting is most consequential for comfort and long-term musculoskeletal risk.

5. Conclusions. This paper presented a comprehensive calibration and experimental validation of an 8-DOF occupant-wheelchair vibration model capable of capturing coupled biomechanical and structural dynamics over the frequency range of 0-20 [Hz]. Four metaheuristic optimization strategies, namely GA, PSO, DE and a staged Hybrid GA-PSO-DE framework, were implemented to identify physically consistent stiffness and damping parameters for three representative seat-cushion archetypes: Jay J2 Deep Contour (gel-based), ROHO High Profile (air-based), and Comfort Mate Foam (foam-based). The Hybrid GA-PSO-DE approach consistently produced the lowest normalized cost ($J_{\text{avg}} \approx 0.11$), the smallest transmissibility error ($\text{RMSE}_{|\Delta T|} \approx 0.045$), and the highest experimental agreement (94-96[%]), while all identified solutions satisfied the stability requirement ($\lambda > 0$) with positive-definite mass, damping, and stiffness matrices, ensuring mechanical feasibility and physiological coherence.

The comparative results reveal a clear material-dependent hierarchy in vibration attenuation performance. The gel-based cushion, characterized by relatively low stiffness ($k_4 \approx 37$ [kN/m]) and moderate damping ($c_4 \approx 508$ [N·s/m]), provided strong isolation near the 3-3.5 [Hz] torso-spine resonance but exhibited increased sensitivity to low-frequency excitation. The pneumatic ROHO cushion achieved a balanced response through intermediate stiffness and damping ($k_4 \approx 77$ [kN/m]; $c_4 \approx 688$ [N·s/m]), resulting in broadband comfort and smooth phase recovery. In contrast, the viscoelastic foam cushion, with the highest stiffness ($k_4 \approx 115$ [kN/m]) and damping ($c_4 \approx 1.15 \times 10^3$ [N·s/m]), provided effective attenuation beyond 6 [Hz] and superior postural stability. These findings

confirm that vibration comfort and isolation can be systematically optimized by appropriately balancing the stiffness-damping ratio across different cushion materials.

From an algorithmic perspective, the Hybrid GA-PSO-DE framework demonstrated superior robustness for high-dimensional inverse parameter identification by integrating global exploration, adaptive convergence, and local refinement. The identified damping ratios ($\zeta = 0.18\text{-}0.32$) and relaxation times ($\tau = (4.4\text{-}9.9) \times 10^{-3}$ [s]) remained physically meaningful and closely matched experimentally observed relaxation behavior, underscoring the framework's reliability beyond purely numerical convergence.

Importantly, accurate prediction of the primary resonance within the physiologically sensitive 3-4 [Hz] band enables health-oriented wheelchair configuration consistent with ISO 2631-1 frequency-weighted evaluation principles. By facilitating targeted damping enhancement and stiffness placement, the proposed framework supports vibration mitigation strategies focused on reducing amplification in the most critical biodynamic region.

Beyond engineering validation, the identified damping-ratio range provides a practical personalization index for clinical seating selection. For individuals at elevated risk of vibration-induced spinal discomfort, cushions yielding higher effective damping ratios may be preferentially selected to suppress resonance amplification, whereas higher stiffness may be prioritized when postural stability is the dominant requirement, provided that sufficient damping is maintained to avoid resonance magnification.

Future work will extend the present model toward multi-axis vibration coupling, frequency-dependent viscoelasticity, and preload-sensitive contact representations for pneumatic and polymeric systems. Incorporating multi-objective optimization, uncertainty quantification, and real-road excitation will further enhance predictive fidelity. Overall, the proposed Hybrid GA-PSO-DE-based 8-DOF framework establishes a scientifically rigorous and practically applicable foundation for next-generation wheelchair design, personalized comfort evaluation, and vibration-exposure mitigation.

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