Optimization of electric vehicle suspension parameters using Improved Artificial Fish Swarm Algorithm

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ABSTRACT

This study proposes a solution to reduce vertical vibrations and body pitching in response to random road surface excitations. To achieve these objectives, a half-vehicle model of an electric vehicle (EV) is developed to determine optimal parameters for both the EV suspension system and the driver's seat suspension system. An Improved Artificial Fish Swarm Algorithm (IAFSA) is implemented using MATLAB software to optimize these suspension parameters. The optimization aims to minimize the root mean square (RMS) values of three objective functions: vertical driver's seat acceleration (a_{ws}), vertical vehicle body acceleration (a_{wb}), and pitching vehicle body acceleration (a_{wphi}). The optimization results reveal that the values of these three objective functions decrease when using the optimized suspension parameters compared to the original suspension settings. Specifically, the a_{ws}, a_{wb} and a_{wphi} values are reduced by 15.44%, 11.46%, and 8.65%, respectively, when the vehicle travels on an ISO road class B at a speed of 20 m/s with a full load. Furthermore, the peak amplitude values of a_s, a_b, and a_{phi} in the frequency domain are also reduced with the optimized suspension parameters compared to the original settings under the specified conditions.

Keywords: Electric vehicle; Suspension parameters; Optimization; IAFSA.

1. INTRODUCTION

The suspension system in vehicles, including electric vehicles (EVs), plays a crucial role in managing vibrations and enhancing ride comfort and safety by isolating the vehicle body from road disturbances. There are three primary types of suspension systems used in vehicles, including passive, active, and semi-active [1]. Passive suspensions are relatively inexpensive, reliable, and easy to maintain, but they have limited capability in vibration isolation and ride comfort [2, 20, 21, 24, 25]. Active suspension systems utilize sensors, actuators, and control units to adjust suspension characteristics in real-time, adapting automatically to different road conditions and providing superior ride comfort and handling performance [3, 4]. However, these systems are complex, expensive, and require a significant amount of energy, which can be a challenge for electric vehicles. Semi-active suspension systems offer a middle ground between passive and active systems, using variable dampers that adjust their damping characteristics in response to road conditions and vehicle dynamics [5, 6]. Various control strategies have been developed to enhance suspension performance in EVs. Common methods include Fuzzy Logic Control [7], PID Control [8], Linear Quadratic Regulator (LQR) Control [9], Neural Network Control [10], Sliding Mode Control (SMC) [11], and Model Predictive Control (MPC) [12]. Fuzzy Logic Control is robust and adaptive but can be challenging to design optimally for all scenarios. PID Control is simple and widely used, but its performance is limited in handling complex dynamics. LQR minimizes a cost function representing the trade-off between ride comfort and suspension deflection, yet it requires accurate mathematical models and is sensitive to parameter variations. MPC provides a framework for optimizing performance but is computationally intensive, which may limit real-time application in EVs. Given these limitations, optimizing the design parameters of suspension systems offers a simpler and potentially more effective solution. By optimizing parameters such as spring stiffness and damping coefficient characteristics using optimization techniques like Genetic Algorithms (GA) [13, 18, 19]. Particle Swarm Optimization (PSO) [14], and the Firefly Algorithm (FA) [15], an optimal balance between ride comfort and handling performance can be achieved. Recently, the Artificial Fish Swarm Algorithm (AFSA) has garnered significant attention for its effectiveness in solving complex optimization problems. Its advantages, including flexibility, high convergence speed, accuracy, and fault tolerance, make it a valuable tool. Therefore, this study applies an improved AFSA-based optimization algorithm to optimize the suspension parameters for an electric vehicle.

2. THE DYNAMIC MODEL OF ELECTRIC VEHICLE

The half-vehicle dynamic model of the electric vehicle is illustrated in figure 1, which includes the vertical motion of the driver's seat, the vehicle body, and vehicle axle masses. Additionally, there is a pitch motion of the vehicle body around its center.

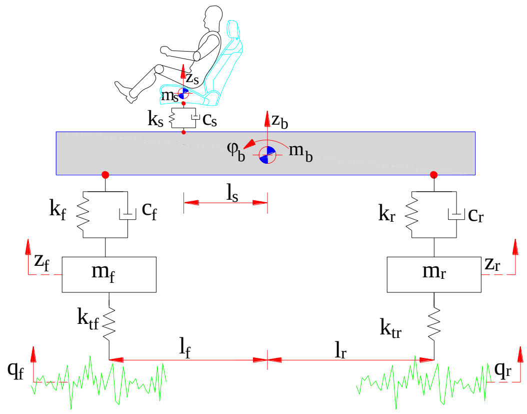

***Figure 1.** Electric vehicle model.*

In figure 1, the symbols m_s, m_b, m_f, and m_r represent the masses of the driver's seat, vehicle body, front axle, and rear axle, respectively. The symbol φ_b denotes the pitch angle of the vehicle body. z_s, z_b, z_f, and z_r indicate the vertical displacements of the driver's seat mass, vehicle body mass, and front and rear axle masses, respectively. Additionally, k_f, k_r *and* c_f, c_r represent the spring stiffness and damping coefficients of the front and rear suspension systems, while k_{tf} and k_{tr} denote the stiffness of the front and rear tires. Lastly, k_s and c_s refer to the stiffness and damping coefficients of the driver's seat.

Based on the Newton laws, the motion equations of EV could be written by

$$m_s\ddot{z}_s = -[k_s(z_s - z_{sb}) + c_s(\dot{z}_s - \dot{z}_{sb})] \tag{1}$$

The vertical motion equation of the vehicle body is written by

$$\begin{aligned} m_b\ddot{z}_b = {} & [k_s(z_s - z_{sb}) + c_s(\dot{z}_s - \dot{z}_{sb})] - [k_f(z_{bf} - z_f) + c_f(\dot{z}_{bf} - \dot{z}_f)] \\ & - [k_r(z_{br} - z_r) + c_r(\dot{z}_{br} - \dot{z}_r)] \end{aligned} \tag{2}$$

The body pitch motion equation of the vehicle body is written by

$$\begin{aligned} I_b\ddot{\varphi}_b = {} & \left[k_f(z_{bf} - z_f) + c_f(\dot{z}_{bf} - \dot{z}_f)\right]l_f - \left[k_r(z_{br} - z_r) + c_r(\dot{z}_{br} - \dot{z}_r)\right]l_r \\ & - \left[k_s(z_s - z_{sb}) + c_s(\dot{z}_s - \dot{z}_{sb})\right]l_s \end{aligned} \tag{3}$$

The vertical motion equation of the front axle is written by

$$m_f \ddot{z}_f = \left[k_f (z_{bf} - z_f) + c_f (\dot{z}_{bf} - \dot{z}_f) \right] - k_{tf} (z_f - q_f) \quad (4)$$

The vertical motion equation of rear axle is written by

$$m_r \ddot{z}_r = \left[k_r (z_{br} - z_r) + c_r (\dot{z}_{br} - \dot{z}_r) \right] - k_{tr} (z_r - q_r) \quad (5)$$

The vertical displacement of the two points of the vehicle body

$$z_{sb} = z_b - l_s \varphi_b ; z_{bf} = z_b - l_f \varphi_b ; z_{br} = z_b + l_r \varphi_b \quad (6)$$

Road surface excitation: The road surface conditions according to ISO 8608: 2016 [22] are selected as excitation functions for vehicle - road coupled interaction model of an EV which is defined as

$$q(t) = \sum_{i=1}^{N} \sqrt{2G_d\left(n_i\right)\Delta n_i} \cos\left(2\pi i \Delta n t + \beta_i\right) \quad (7)$$

Where: $G_d(n_i)$ is the power spectral density (PSD) at frequency n_i which is defined from ISO class A to ISO class H according to ISO 8608: 2016; Δn_i is the variance of the road surface profile which depends on the spatial frequency and the time step; β_i is the phase of the harmonic function (rad) which is randomly generated between 0 and π.

3. OPTIMIZING THE DYNAMIC PARAMETERS

3.1. The improved artificial fish swarm algorithm

In a conventional AFSA- Artificial fish swarm algorithm[16], the algorithm typically conducts a random search within its visual range for the next state, leading to several disadvantages. This method is time-consuming as it explores all directions until it finds the next position. Additionally, the randomness results in a jagged trajectory with unnecessary zigzag turns. To address these issues, a heuristic directional operator is introduced, prompting the AFSA to actively choose the best position during prey behavior. Let *P* represent the set of all potential positions, with X_j being the *j-th* possible position of the *i-th* artificial fish in its step range [17].

$$P = \left\{ X_{i,j}^{p} \mid X_{i,j}^{p} - X_i \leq \text{ Step}, i\text{=1,2,3,...}N, j\text{=1,2,3...,M} \right\} \quad (8)$$

In the prey behavior process, the food concentration at potential positions within P is calculated, and the best position $X^{p}{}_{i,best}$ is chosen for the next move. The directional operator allows the AFSA to find the optimal position in a single calculation cycle, greatly reducing computational time and eliminating unnecessary random searches and redundant points [17].

$$X^{p}{}_{i,best} = \min\left\{ f(X^{p}{}_{i,1}), f(X^{p}{}_{i,3}), f(X^{p}{}_{i,3}) .... f(X^{p}{}_{i,M}) \right\} \quad (9)$$

$$X_i(t+1) = X_i(t) + \frac{X^{p}{}_{i,best}(t) - X_i(t)}{X^{p}{}_{i,best} - X_i(t)} \text{ x } Step \text{ x } rand() \quad (10)$$

Eliminating the random process reduces the adaptability of the AFSA, making it prone to local optima. To counter this, a probability weight factor is introduced based on the Bernoulli distribution. This allows the algorithm to exhibit random behavior intermittently, helping it escape local optima [17].

$$X_i(t+1) = \begin{cases} X_i(t) + \dfrac{X^{p}{}_{i,best}(t) - X_i(t)}{X^{p}{}_{i,best} - X_i(t)} \text{ x } Step \text{ x } rand() \text{ , } m = 0 \\ X_i(t) + \dfrac{X_j(t) - X_i(t)}{X_j(t) - X_i(t)} \text{ x } Step \text{ x } rand() \text{ , } m = 1 \end{cases} \quad (11)$$

In a typical AFSA, constant visual and step sizes can hinder performance. Larger values enhance initial convergence speed but may lead to local optima or iterative jumps, while smaller values decrease efficiency. Adjustments to these sizes at different stages are necessary. To balance global search and convergence speed, an adaptive factor is used. For N artificial fish $F_i(i=1,2,3,\ldots,N)$, the visual is calculated using a weighted average based on distances D_{ij} and weight factors v_{ij} [17].

$$V_i = \frac{\sum_{i=1, i\neq j}^{N} D_{\mathrm{ij}} \times \omega_{\mathrm{ij}}}{\sum_{i=1, i\neq j}^{N} \omega_{\mathrm{ij}}} \tag{12}$$

$$Step = Step \times \left(1 - \frac{i}{MaxIter}\right) \tag{13}$$

3.2. Optimal target and constraint selection

To enhance the ride comfort of the electric vehicle, the RMS values of vertical seat acceleration, and vertical and pitching body accelerations are selected as the optimization objectives. During the optimization process, the suspension parameters such as [k_s, k_f, k_r, c_s, c_f, c_r] are selected to be optimized. The objective function is formulated as follows

$$minJ = \alpha_1 \frac{SA(X)}{SA_{pass}} + \alpha_2 \frac{BA(X)}{BA_{pass}} + \alpha_3 \frac{PA(X)}{PA_{pass}} \tag{14}$$

where, *SA(X)*, *BA(X)*, and *PA(X)*, represent the a_{ws}, a_{wb} and a_{wphi} values to be optimized, respectively. It should be noted that the a_{ws}, a_{wb} and a_{wphi} values must be lower than their values before optimization. Therefore, the optimization conditions are as follows:

$$st \begin{cases} SA(X) < SA_{pass} \\ BA(X) < BA_{pass} \\ PA(X) < PA_{pass} \end{cases} \tag{15}$$

In the above formula, SA_{pass}, BA_{pass}, PA_{pass} are the a_{ws}, a_{wb} and a_{wphi} values before optimization. *X* represents the variables to be optimized. The range for these optimization variables is as follows: 10800 N/m $\leq k_s \leq$ 19200 N/m; 1125 N.s/m $\leq c_s \leq$ 1625 N.s/m; 14080 N/m $\leq k_f \leq$ 21120 N/m; 1275 N.s/m $\leq c_f \leq$ 1950 N.s/m; 17840 N/m $\leq k_r \leq$ 27760 N/m; 1445 N.s/m $\leq c_r \leq$ 2210 N.s/m.

4. RESULTS AND DISCUSSION

To optimize suspension parameters for an EV, Matlab/Simulink software is selected to simulate and find out the optimal suspension parameters with the EV parameters in table 1 using the IAFSA code. The effectiveness of the IASFA with the standard ASFA is shown in Fig.2. The optimal suspension parameters of EV are shown in table 2.

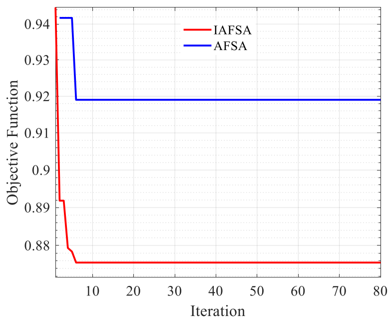

Figure 2. *Convergence of the algorithm between IASFA and ASFA.*

The optimized parameters with IASFA are compared with the original suspension system of EV when the vehicle moves on ISO road class B at a speed of 20 m/s and full load, the a_s, a_b and a_{phi} values with both time and frequency domains are shown in Fig. 3. From the a_s, a_b and a_{phi} values on the time domains in Fig.3, the a_{ws}, a_{wb} and a_{wphi} values are defined based on ISO 2631 (1997) [23], as shown in table 3.

Table 1. *EV parameters of with original suspension systems.*

Parameter	Unit	Value	Parameter	Unit	Value			
m_s	kg	70	I_b	Kg. m^{-2}	1940	k_r	$(N \cdot m^{-1})$	22300
m_b	kg	1100	k_{tr}	$(N \cdot m^{-1})$	200000	k_s	$(N \cdot m^{-1})$	12000
m_f	kg	60	c_s	$(N \cdot s \cdot m^{-1})$	1250	k_{tf}	$(N \cdot m^{-1})$	180000
m_r	kg	65	c_f	$(N \cdot s \cdot m^{-1})$	1500	l_f/lr	m	1.15/1.30
k_f	$(N \cdot m^{-1})$	17600	c_r	$(N \cdot s \cdot m^{-1})$	1700	l_s	m	0.68

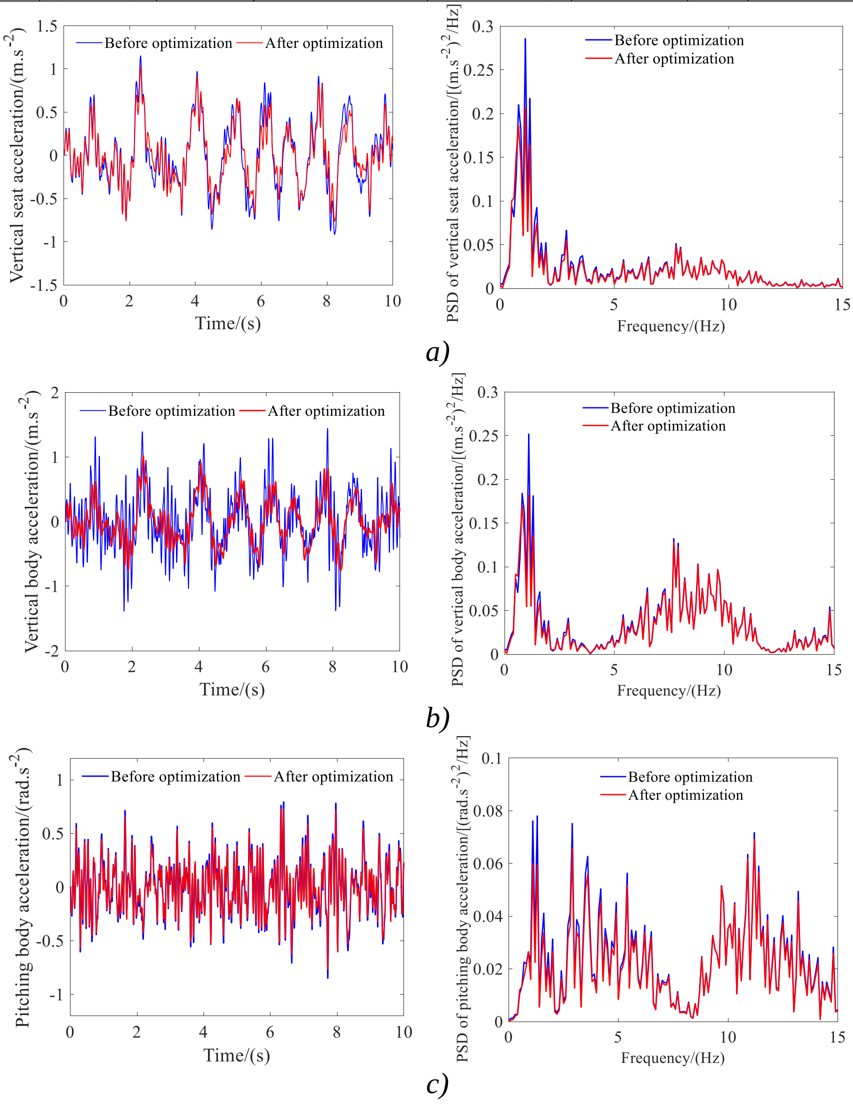

Figure 3. *Performance comparison in the time and frequency domains under random road conditions.*

The results in table 3 indicate that the a_{ws}, a_{wb} and a_{wphi} values with optimal parameters respectively reduce by 15.44%, 11.46% and 8.65% compared to the original suspension parameters. In addition, The results in Fig. 3 indicate that the peak amplitude values of a_s, a_b and a_{phi} on frequency domains respectively reduce compared to the original suspension parameters under the survey condition.

Table 2. *The suspension system parameters were optimized.*

Parameters	Unit	Value	Parameters	Unit	Value
k_s	$(N \cdot m^{-1})$	10800	c_s	$(N \cdot s \cdot m^{-1})$	1270
k_f	$(N \cdot m^{-1})$	14080	c_f	$(N \cdot s \cdot m^{-1})$	1350
k_r	$(N \cdot m^{-1})$	17840	c_r	$(N \cdot s \cdot m^{-1})$	1530

Table 3. *The RMS values of performance indices.*

Performance	Unit	Value		Amplification
		Before optimization	After optimization	(%)
a_{ws}	$m.s^{-2}$	0.4028	0.3406	15.44
a_{wb}	$m.s^{-2}$	0.4644	0.4112	11.46
a_{wphi}	$rad.s^{-2}$	0.2510	0.2293	8.65

5. CONCLUSIONS

In this study, a five-degree-of-freedom dynamic model for an electric vehicle was proposed under random road surface excitation. The optimal suspension parameters are found via the Improved Artificial Fish Swarm Algorithm. Some conclusions drawn from the optimization results (i) the a_{ws}, a_{wb}, and a_{wphi} values with optimal suspension parameters respectively reduce by 15.44%, 11.46%, and 8.65% compared to the original suspension parameters when the vehicle moves on ISO road class B at a speed of 20 m/s and full load and (ii) the peak amplitude values of a_s, a_b and a_{phi} on frequency domains with optimal suspension parameters respectively reduce compared to the original suspension parameters under the survey condition.

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REFERENCES

[1]. I. Dridi *et al*, *"A new approach to controlling an active suspension system based on, reinforcement learning"*, Advances in Mechanical Engineering, Vol. 15, No.6, pp. 1–21, (2023).

[2]. L. R. Miller, *"Tuning passive, semi-active and fully active suspension systems"*, In Proceedings of the 27th IEEE Conference on Decision and Control, Austin, TX, USA, pp. 2047–2053, (1988).

[3]. T. Yoshimura *et al*, *"Construction of an active suspension system of a quarter car model using the concept of sliding mode control"*, Journal of Sound and Vibration, Vol. 239, pp. 187–199, (2001).

[4]. J. Lin *et al*, *"Intelligent control of active suspension systems"*. IEEE Transactions on Industrial Electronics, Vol. 589, pp. 618–628, (2011).

[5]. Y. Shiao *et al*, *"The analysis of a semi-active suspension system"*. In Proceedings of the SICE Annual Conference, Taipei, Taiwan, pp. 1-6, (2010).

[6]. G. Q. B. Tran *et al*, *"Integrated comfort-adaptive cruise and semi-active suspension control for an autonomous vehicle: an lpv approach"*. Electronics, Vol.10, No 7, pp.1-25, (2010).

[7]. A. B. Sharkawy *et al*, *"Fuzzy and adaptive fuzzy control for the automobiles' active suspension system"*. Vehicle System Dynamics, Vol. 43, pp. 795–806, (2005).

[8]. S. R. Pillai *et al*, *"Design of pid control to improve efficiency of suspension system in electric vehicles"*, 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE),Dubai, United Arab Emirates, pp. 670-575, (2019).

[9]. L. Mingjie, *"Research on the safety of intelligent vibration control systemfor electric vehicle suspension"*, Highlights in Science, Engineering and Technology, Vol. 9, pp. 248-253, (2022).

[10]. I. Eski *et al*, *"Vibration control of vehicle active suspension system using a new robust neural network control system"*. Simulation Modelling Practice and Theory, Vol.17, pp. 778–793, (2009).

[11]. V. Karaman *et al*, *"Sliding mode control of vehicle suspension system under different road conditions"*, International Journal of Engineering Science And Application, Vol.1, No.2, pp. 72-77, (2017).

[12].H. Jiang *et al, "Hybrid model predictive control of semiactive suspension in electric vehicle with hub-motor"*, Applied Sciences, Vol.11, No.1, pp. 1-23, (2021).
[13].X. Shao *et al, "Enhanced ride performance of electric vehicle suspension system based on genetic algorithm optimization"*, 2017 20th International Conference on Electrical Machines and Systems (ICEMS), Sydney, NSW, Australia, pp.1-6, (2017).
[14].L. R. C. Drehmer *et al, "Parameters optimisation of a vehicle suspension system using a particle swarm optimisation algorithm"*, Vehicle System Dynamics, pp.449-474, (2015).
[15].M. J. Mahmoodabadi *et al, "Firefly algorithm based optimum design of vehicle suspension systems"*, International Journal of Dynamics and Control, Vol. 7, pp.134–146, (2019).
[16].F. Pourpanah, *"A review of artificial fish swarm algorithms: recent advances and applications"*, Artificial Intelligence Review, Vol.56, pp. 1867–1903, (2023).
[17].L. Zhao et al, *"Route planning for autonomous vessels based on improved artificial fish swarm algorithm"*, Ships and Offshore Structures, Vol.18, pp. 897-906, (2023).
[18].N. V. Tuan et al, *"Optimal design parameters of air suspension systems for semi-trailer truck. Part 1: modeling and algorithm"*, Vibroengineering PROCEDIA, Vol. 33, pp. 72–77, (2020).
[19].N. V. Tuan et al, *"Optimal design parameters of air suspension systems for semi-trailer truck. Part 2: results and discussion"*, Vibroengineering PROCEDIA, Vol. 33, pp. 147–152, (2020).
[20].L. X. Long et al, *"Study on the influence of bus suspension parameters on ride comfort"*, Vibroengineering PROCEDIA, Vol. 21, pp. 77–82, (2018).
[21].Van Quynh, L., et al, *"Effects of suspension design parameters of a semi-trailer truck on vehicle ride comfort and road surface friendliness"*. In: Lecture Notes in Networks and Systems, vol. 104, pp. 281–289, (2018).
[22].ISO 8068, *"Mechanical Vibration-Road Surface Profiles – Reporting of Measured Data"*. (2016).
[23].ISO 2631-1, *"Mechanical Vibration and Shock-Evaluation of Human Exposure to Whole Body Vibration-Part 1: General Requirements"*, (1997).
[24].Van Quynh, L., Van Cuong, B., Long, L.X., Van Quan, D. *"Effects of Suspension Design Parameters of a Semi-trailer Truck on Vehicle Ride Comfort and Road Surface Friendliness"*. Lecture Notes in Networks and Systems. Springer, Cham, vol 104, (2020).
[25].L. V. Quynh *et al, "Effect of in-wheel motor suspension system on electric vehicle ride comfort"*. Vibroengineering PROCEDIA, Vol. 29, pp. 148–152, (2019).

TÓM TẮT

Tối ưu hóa các thông số thiết kế hệ thống treo xe điện sử dụng thuật toán đàn cá nhân tạo cải tiến

Nghiên cứu này đề xuất một giải pháp để giảm dao động theo phương thẳng đứng và lắc dọc thân xe dưới kích thích mặt đường ngẫu nhiên. Để đạt được mục đích này, một mô hình động lực học 1/2 xe của một xe điện đã được thiết lập để tìm kiếm các thông số tối ưu cho hệ thống treo của xe và hệ thống treo ghế ngồi người điều khiển. Một thuật toán đàn cá nhân tạo cải tiến (IAFSA) được áp dụng trong phần mềm MATLAB để tối ưu hóa các thông số các hệ thống treo của xe của xe và ghế ngồi người điều khiển. Quá trình tối ưu hóa tập trung vào việc giảm giá trị bình phương bình (RMS) của ba hàm mục tiêu, bao gồm gia tốc thẳng đứng của ghế ngồi người điều khiển (a_{ws}), gia tốc thẳng đứng tại vị trí thân xe (a_{wb}) và gia tốc lặc dọc thân xe (a_{wphi}). Các kết quả tối ưu cho thấy rằng các giá trị của 3 hàm mục tiêu với các thông số tối ưu của các hệ thống treo lần lượt giảm so với các thông số của các hệ thống treo xe nguyên bản. Đặc biệt các giá trị a_{ws}, a_{wb} và a_{wphi} với các thông số tối ưu lần lượt giảm 15.44%, 11.46% và 8.65% so với các thông số của các hệ thống treo xe nguyên bản khi xe chuyển động trên mặt đường ISO cấp B với vận tốc xe 20 m/s và xe đầy tải. Ngoài ra, các giá trị biên độ a_s, a_b và a_{phi} với với các thông số tối ưu lần lượt giảm so với các thông số của các hệ thống treo xe nguyên bản dưới điều kiện khảo sát.

Từ khoá: Xe điện; Thông số hệ thống treo; Tối ưu; IAFSA.