

Original Article

Quasi-Steady Roll Plane Analysis and Metaheuristic Optimization for Enhancing Lateral Stability of Electric Vehicles using Active Height Control

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Abstract - With the increasing adoption of Electric Vehicles (EVs), the need for ensuring safe driving arises obviously. Though the EVs are designed to have a lower Center of Gravity (CG) height compared to Internal Combustion Engine Vehicles (ICEVs), due to their dynamic operating and road conditions, probabilities of rollover risk prevail. In order to ensure lateral stability and mitigate rollover risk, this paper presents the application of a metaheuristic optimization method to get the optimal key design parameters, one of which is the CG height, which is used as a reference signal to the Model Predictive Controller (MPC) of an Active Height Control (AHC) system comprising a hydraulic active suspension system at each of the wheels. The key parameters that influence the quasi-steady lateral acceleration are first optimized using the Shuffled Frog Leaping Algorithm (SFLA), and the results are benchmarked against the Genetic Algorithm (GA) to prove the salient feature of SFLA. A constrained Model Predictive Control (MPC) system that could estimate the disturbance and track the CG height offset-free is developed to modulate the vehicle's CG height to the SFLA reference. The SFLA, GA and MPC are simulated using MATLAB coding. Simulation results of SFLA and GA are tabulated. The AHC system simulation results demonstrate that the proposed approach effectively maintains the CG height near its optimal value while minimizing lateral acceleration. Furthermore, the rollover index is also significantly reduced, remaining well below critical safety thresholds. An experimental demonstration comprising a LVDT with a metric micrometer to emulate measurement of CG height in real-time, associated signal conditioning circuit to derive a usable voltage and a servo positioning system to emulate electro-hydraulic valve functioning in the Hydraulic active suspension system is also presented to prove the feasibility of the proposed methods real-time implementation and control.

Keywords - Active Height Control (AHC), Electric Vehicles, Genetic Algorithm (GA), Lateral stability, Metaheuristic optimization, Shuffled Frog Leaping Algorithm (SFLA), Vehicle dynamics.

1. Introduction

The rapid growth of Electric Vehicles (EVs) has introduced new challenges in vehicle dynamics and stability due to their unique structural and operational characteristics. In general, EVs are characterized by a lower Centre of Gravity (CG) compared to traditional internal combustion engine vehicles due to battery placement. Nevertheless, possibilities of susceptibility to lateral instability and rollover exist during aggressive manoeuvres, owing to their dynamic operating and road conditions. Therefore, ensuring vehicle stability in the face of such dynamic conditions has become a critical research focus in modern automotive engineering [7, 9, 28, 37].

Lateral stability is mainly affected by parameters such as track width, height of the CG, height of the roll centre and suspension characteristics. These parameters have direct impacts on the lateral acceleration and the rollover attitude of the vehicle [3, 9, 19]. The traditional passive suspension

systems are limited to adapt to different road and driving conditions, and the advanced active control systems need to be developed. Among these, Active Height Control (AHC) systems have received great interest due to their potential of dynamically adjusting the vehicle CG height to improve the stability and ride performance [27, 28, 31, 45].

Recent research activities have investigated different control approaches such as the Proportional-Integral-Derivative (PID) control and the Model Predictive Control (MPC) for the improvement of vehicle stability. Of these, MPC has emerged as a powerful tool due to its ability to handle multi-variable systems, constraints and predictive behaviour [44, 46, 47].

Furthermore, the application of the Model Predictive Control (MPC) in the integrated lateral stability, traction control and rollover prevention in electric vehicles has been



successfully demonstrated [7, 9, 10, 22]. However, the effectiveness of such control strategies majorly depends on the optimal selection of system parameters. The classical convex optimisation admits a unique global optimum for some specific well-behaved problems [8]. But the prevailing is a nonlinear optimization problem of complex.

Metaheuristic optimization techniques have been shown to be very effective to solve such complex optimization problems [1, 23, 24]. The Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Shuffled Frog Leaping Algorithm (SFLA) are robust search algorithms with global convergence properties. Specifically, SFLA combines the merits of memetic evolution and social behavior, which make it suitable for engineering optimization problems with many constraints and nonlinearities [2, 30].

This study proposes a metaheuristic optimization framework based on SFLA to identify the optimal parameters affecting quasi-steady lateral stability in Electric Vehicles (EVs). To make sure that SFLA works, it is compared to GA. Then, the optimized parameters are used to make a real-time control strategy for an AHC system. A constrained Model Predictive Control (MPC) scheme featuring disturbance estimation and offset-free tracking is employed to dynamically regulate the CG height under fluctuating operating conditions, in accordance with recent developments in predictive stability control frameworks [5, 7, 9, 10, 22].

Additionally, a soft-constrained MPC formulation with slack variables is used to make sure that the system is strong and works well even when things change, like when the road is bumpy or the load shifts. Simulation studies are used to test how well the proposed method works, and performance is measured using widely used measures of vehicle stability, such as lateral acceleration and rollover index.

The results show that the vehicle's stability and safety have improved a lot. An experimental demonstration of the sensing technology for CG height drift measurement using LVDT and electro-hydro valve activation using a servo motor are presented to show the practical feasibility of implementation in real-time, consistent with modern sensor-based vehicle state estimation approaches. The major contributions of this work are as follows:

- Development of a metaheuristic optimization using SFLA to derive the optimal key design parameters and benchmark it against GA.
- Sensitivity analysis to narrow down the key design parameter to be fed as reference to offset-free constrained MPC for AHC systems with disturbance estimation.
- Validation of the lateral stability simulation results using the rollover index thresholds.
- An experimental demonstration to prove the feasibility of real-time implementation avenues.

In concise, the proposed methodology presents metaheuristic based optimal design parameter fed as reference to the AHC system to enhance the lateral stability of electric vehicles and experimental demonstration to prove the methodology's feasibility for real-time automotive applications.

2. Methodology

Figure 1 presents the proposed work's methodology. It integrates vehicle dynamics modelling, optimization, and real-time control to actively enhance vehicle stability by regulating the Centre of Gravity (CG) height.

The process begins with a vehicle dynamics model, where the roll behaviour of the vehicle is mathematically represented for a quasi-steady state. Such models are widely used to capture lateral and roll dynamics using simplified representations like the single-track or bicycle model [35], [36]. A relationship comprising the lateral acceleration ratio (a_y/g), which is a measure of stability index, governed by key parameters as mentioned in Equation (3), which is presented in most of the literature [16, 38, 39] is considered to quantify the rollover attitude.

This stability index is used in a metaheuristic optimization framework that combines SFLA and Genetic Algorithm (GA) to find the best CG height (h_{ref}) that reduces the risk of rollover while still meeting performance standards for the vehicle. Metaheuristic methods like GA and SFLA are popular in engineering for solving nonlinear, constrained optimization problems because they can search the whole space and are reliable [4, 17]. This ideal value is the point of reference for control.

The system uses a sensor-based CG estimation module (based on LVDT measurements) to figure out the current CG height while it is running. For accurate vehicle state monitoring, these kinds of estimation methods, which are often backed up by sensor fusion and state estimation techniques, are very important. The simulation assumes that the real CG height is 0.8 m with noise modulation. An error signal is the difference between the desired and estimated CG heights.

A Model Predictive Controller (MPC) for Active Height Control (AHC) then fixes this error. The MPC anticipates forthcoming system behavior and produces optimal control inputs while accommodating system constraints. Recent studies [18, 19] have shown that it works well for controlling vehicle dynamics, especially when the conditions are nonlinear and limited.

The controller actively changes the suspension system to control the CG height, which makes the vehicle more stable when it rolls over and keeps it safe to drive.

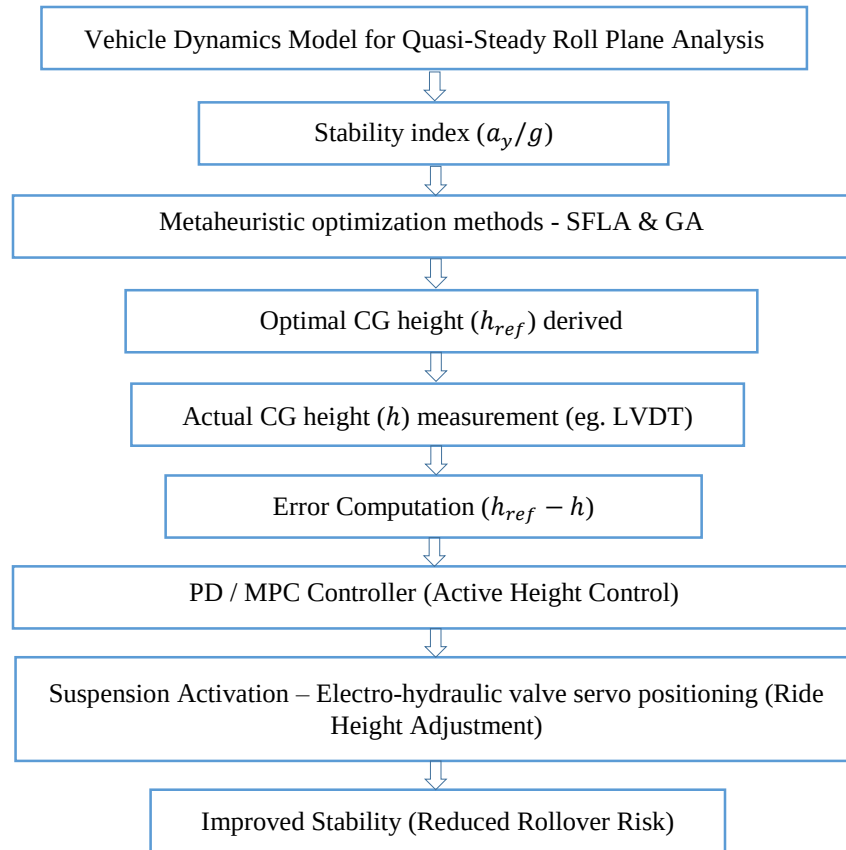


Fig. 1 Proposed methodology

3. Quasi-Steady Roll Plane Analysis

In order to reiterate the rollover threshold of a suspended vehicle, depending on which the proposed system is

developed, the foregoing analysis is referenced from classical vehicle dynamics formulations and rollover modelling approaches reported in the literature [16, 34, 38, 49].

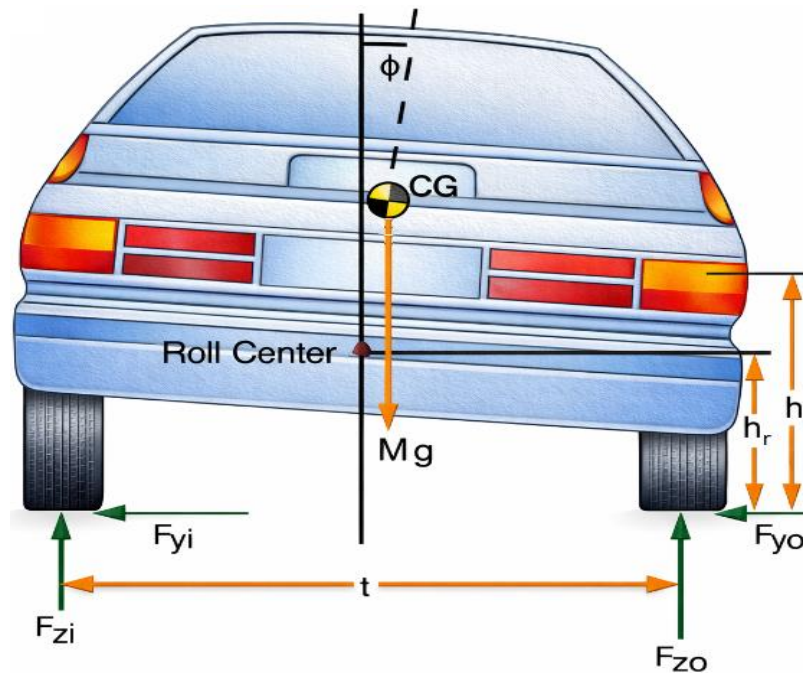


Fig. 2 Roll reactions of a suspended vehicle

The following nomenclatures are used in the analysis:

- M_o - moment about outer wheel contact point
 M_s - sprung mass of the vehicle
 a_y - lateral acceleration
 h - height of the center of gravity above the ground
 g - gravitational acceleration constant
 t - Tread
 ϕ - roll angle of the sprung mass
 h_r - Height of the roll center above the ground at the longitudinal CG location
 R_ϕ - roll gradient

Figure 2 presents the roll reactions on a suspended vehicle. The rollover threshold is derived by considering moment equilibrium about the point O, where the right wheel contacts the ground, and assuming the left wheel load has gone to zero at the onset of rollover. This approach is in agreement with classical moment equilibrium-based rollover formulations. The equilibrium condition is given by Eq. 1, considering the point O:

$$\sum M_o = 0 = M_s a_y h - M_s g \left[\frac{t}{2} - \phi(h - h_r) \right] \quad (1)$$

The terms in the equation physically represent overturning moment (due to lateral acceleration), restoring moment (gravity) and roll-induced reduction in stability respectively. This interpretation is consistent with the suspended vehicle rollover models considering the effects of the rigid-body and suspension. The overturning moment caused by the side acceleration is balanced by the restoring moment caused by gravity. Rearranging Equation (1) and simplifying yields Equation (2).

$$\frac{a_y}{g} = \frac{1}{h} \left[\frac{t}{2} - \phi(h - h_r) \right] \quad (2)$$

Expanding Equation (2) and substituting the roll angle in terms of its definition of roll rate times the lateral acceleration and rearranging yields Equation (3):

$$\frac{a_y}{g} = \frac{t}{2h} \frac{1}{[1 + R_\phi(1 - h_r/h)]} \quad (3)$$

Equation (3) defines the normalized lateral acceleration (rollover threshold) as a function of the principal vehicle parameters, including track width (t), centre of gravity height (h), roll centre height (h_r), and roll rate (R_ϕ).

Similar formulations have been reported widely in the literature for the evaluation of rollover attitude in suspension vehicles [42, 43, 51].

The derived relation shows that an increase of track width increases the stability, while an increase of the CG height or

roll gradient has a negative effect on the rollover resistance. Thus, to enhance the stability of the vehicle and mitigate rollover in cornering, the lateral acceleration should be minimized under bounded constraints exerted on the governing parameters.

This is done by finding out the optimal parameter set using metaheuristic optimization techniques such as Shuffled Frog Leaping Algorithm (SFLA) and Genetic Algorithm (GA). These methods are well-suited to solve nonlinear, constrained optimization problems in vehicle dynamics applications [24]. Moreover, sensitivity analysis is performed to find out the most influential parameters on rollover stability.

4. Metaheuristic Optimization

4.1. SFLA Optimisation

The SFLA is one of the memetic metaheuristic optimisation methods which is based on the foraging characteristics of frogs. It features local search in sub-populations (memeplexes) and global content transfer (shuffling) to solve optimisation problems.

In SFLA, the initial population of candidate solutions are called the 'frogs'. They are generated and evaluated using a defined fitness function. Then the population is split up into sub-populations called the memeplexes.

The local search is performed in sub-populations. It is an iterative process where the worst solutions are updated with the best ones.

In the algorithm, the memeplexes are shuffled to ensure global mixing to avoid premature convergence. By combining the local search and global shuffling, SFLA efficiently solves the nonlinear optimisation problems [2, 23, 30] and can be applied for the proposed method. In this work, each frog in the SFLA population represents a candidate set of vehicle design parameters given by Equation (4):

$$x = [t, h, h_r, R_\phi] \quad (4)$$

The fitness of each candidate is evaluated using a stability index derived from roll plane dynamics, which quantifies the rollover threshold of the vehicle [30, 31]. Equation (5) and Equation (6) presents the fitness function and stability index, respectively.

$$\text{Fitness function, } f = \frac{1}{\text{Stability index}} \quad (5)$$

$$\text{Stability index} = \frac{2h}{t} [1 + R_\phi(1 - h_r/h)] \quad (6)$$

This formulation transforms the rollover stability problem into an optimization based one, where maximizing stability is equivalent to minimizing the inverse fitness function [48].

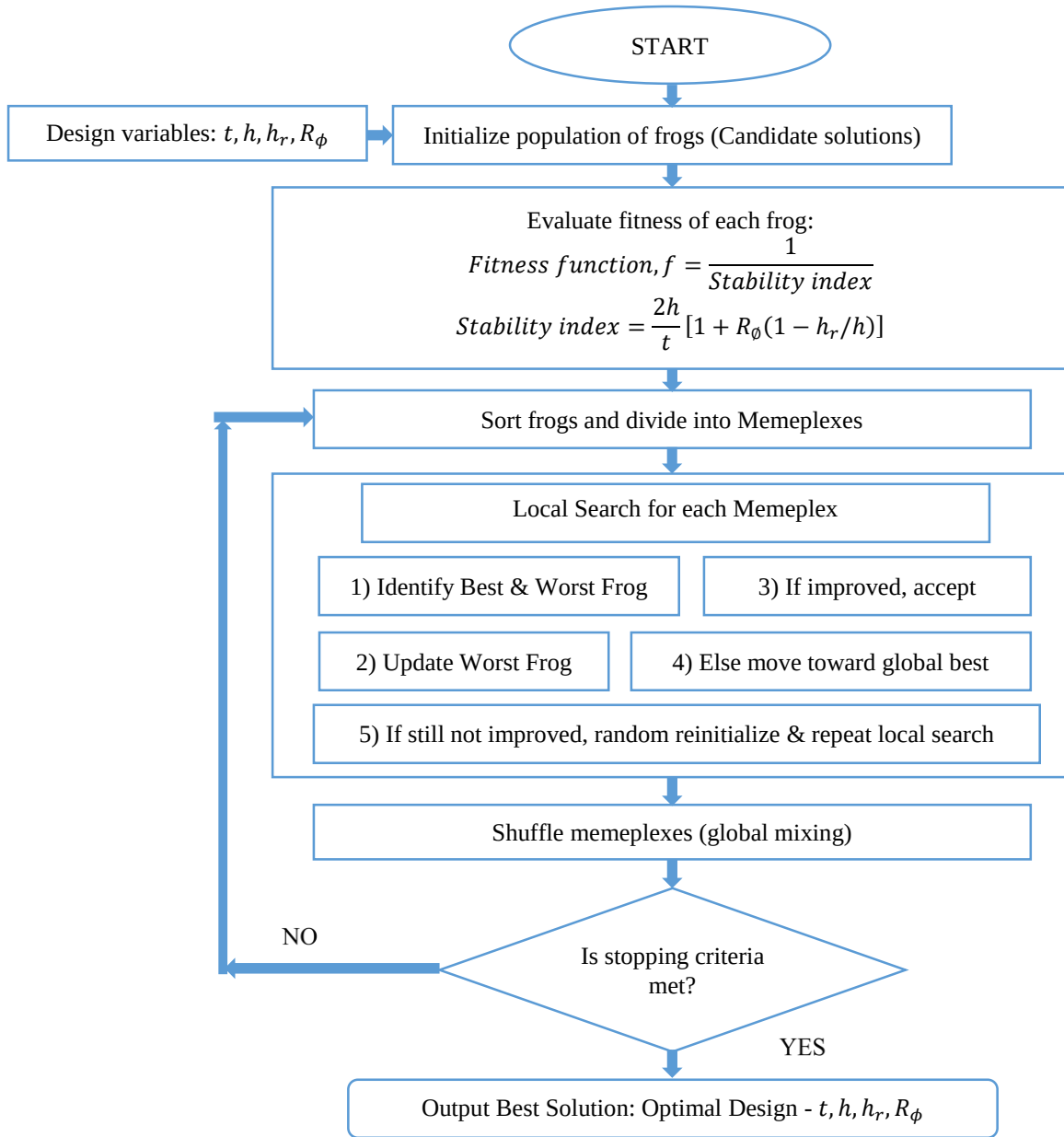


Fig. 3 SFLA flow diagram for the proposed methodology

Figure 3 presents the flow diagram of the SFLA for the proposed methodology. In the proposed optimisation problem, all the design variables are subjected to bound constraints.

This ensures physically realistic and feasible vehicle parameters, which are commonly adopted in vehicle design optimisation studies as presented in Equation (7):

$$\left. \begin{array}{l} 1.55 \leq t \leq 1.7 \\ 0.55 \leq h \leq 0.75 \\ 0.15 \leq h_r \leq 0.3 \\ 0.4 \leq R_\phi \leq 0.8 \end{array} \right\} \quad (7)$$

In addition, physical and safety constraints are imposed to ensure that the roll centre height remains well below the CG height and the vehicle's geometry remains practical as presented in Equation (8):

$$\left. \begin{array}{l} h_r < h \\ h \leq 0.8 \\ t \geq 1.5 \end{array} \right\} \quad (8)$$

Penalty functions are incorporated to address constraint violations as presented in Equation (9). This converts the constrained optimization problem into an unconstrained formulation suitable for metaheuristic optimization.

$$f_{\text{total}} = f + P(x) \quad (9)$$

Where penalty term $P(x)$ is defined as:

$$P(x) = \begin{cases} 10^3 & \text{if bound violated} \\ 10^6 & \text{if } h_r > h \\ 5 \times 10^3 & \text{if soft constraints are violated} \end{cases}$$

The proposed methodology to minimise the lateral acceleration under bounded constraints imposed on the governing parameters as presented in Equations (5) to (8) is simulated. The optimisation process iteratively updates the design variables by guiding poorer solutions toward better-performing ones within each memplexes, as well as periodic shuffling ensuring a global search. This enables the algorithm

to converge toward an optimal combination of geometric and suspension parameters that maximises lateral stability.

Figure 4 presents the convergence of fitness function after 100 iterations. The minimum lateral acceleration is 0.687092 g. Table 1 presents the corresponding results of SFLA optimised design variables.

Table 1. SFLA optimized design variables

Parameters	Optimal Solution
t	1.5698 m
h	0.7307 m
h_r	0.2014 m
R_ϕ	0.7777 radians/g*

* $1g=9.81\text{m/s}^2$

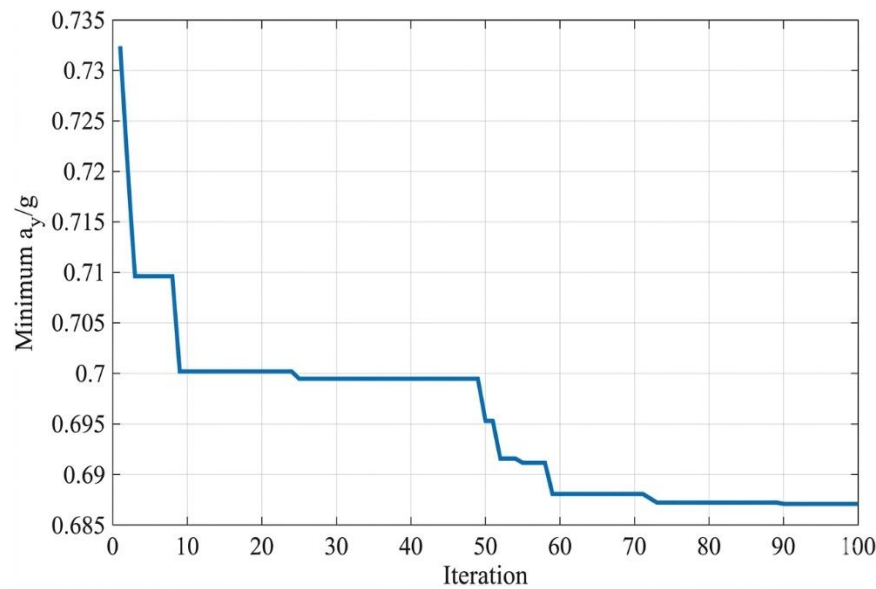


Fig. 4 SFLA convergence characteristics of fitness function

4.2. GA Optimisation

GA is another metaheuristic optimisation method which is inspired by the principles of natural selection and genetics. It features random generation of a population, or a set of candidate solutions. Then it iteratively refines the population by means of selection, crossover, and mutation operators.

The individuals are evaluated at each generation by a fitness function. The fittest solutions are propagated to the next generation. This evolutionary process makes GA a feasible method to solve complex, nonlinear and multi-modal search-based optimisation problems without the need for gradient information [1, 17, 23]. The flow diagram of GA as applied to the proposed methodology is presented in Figure 5.

Due to the robustness and global search capability of GA, it is preferred in the vehicle design and optimization related problems. It includes design optimisation problems, such as

the one proposed in this work, and the other optimisation problems, such as tuning of suspension parameters to enhance vehicle dynamic performance.

The GA first initialises the population of candidate solutions, which are the design variables t , h , h_r and R_ϕ as per the proposed work. The fitness function for each candidate is ascertained by the vehicle's stability index. Selection, crossover and mutation are applied iteratively to evolve the population towards a better solution. This procedure is repeated until the stopping criterion, which is the convergence of the solution, is reached. The optimum values of design parameters that are obtained can be used as input to MPC-based AHC for enhanced lateral stability in vehicular dynamics. Figure 6 presents the convergence of fitness function after 100 iterations. The minimum lateral acceleration is 0.630396 g. Table 2 presents the results of GA optimised design variables.

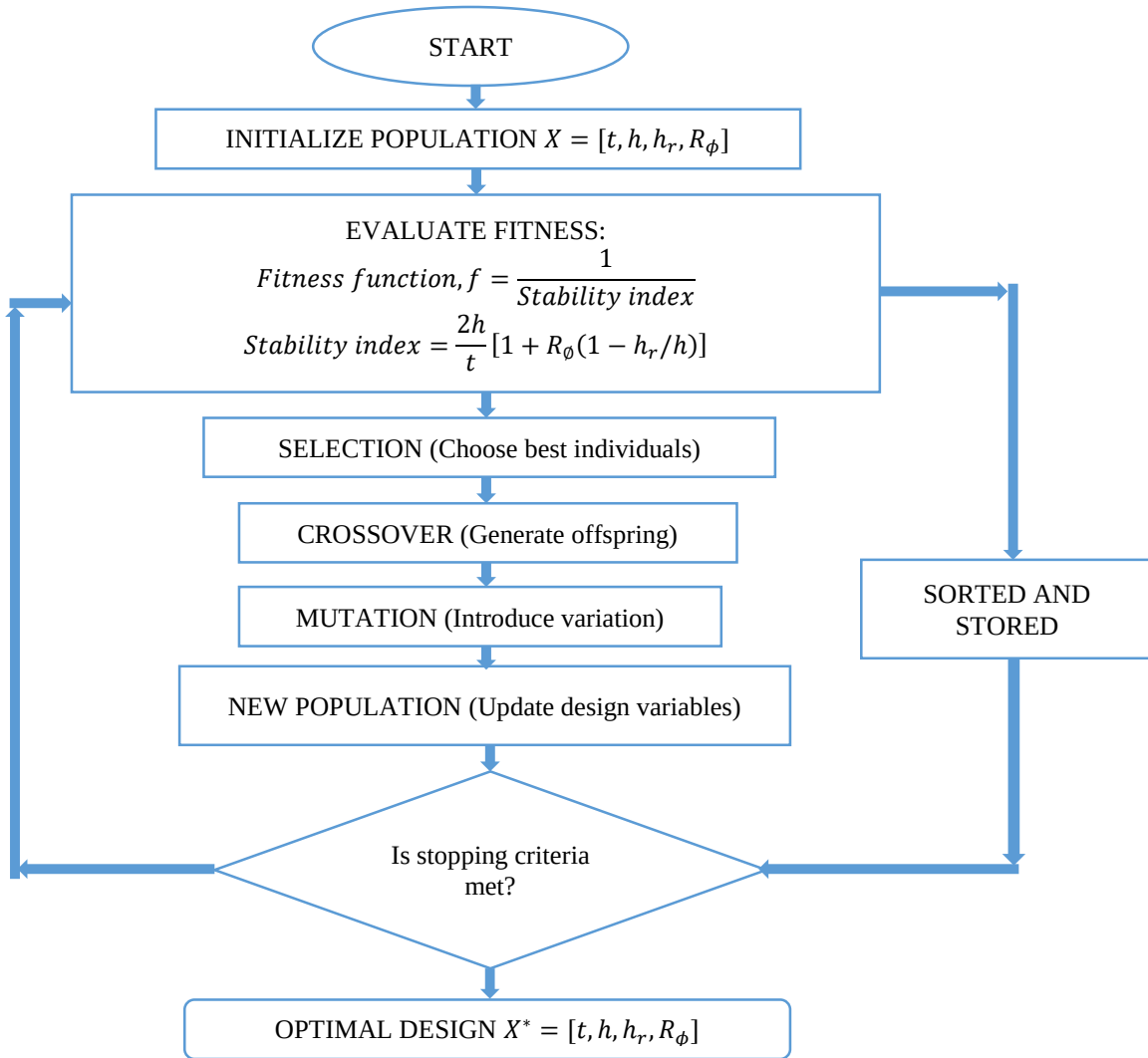


Fig. 5 GA flow diagram as applied to the proposed methodology

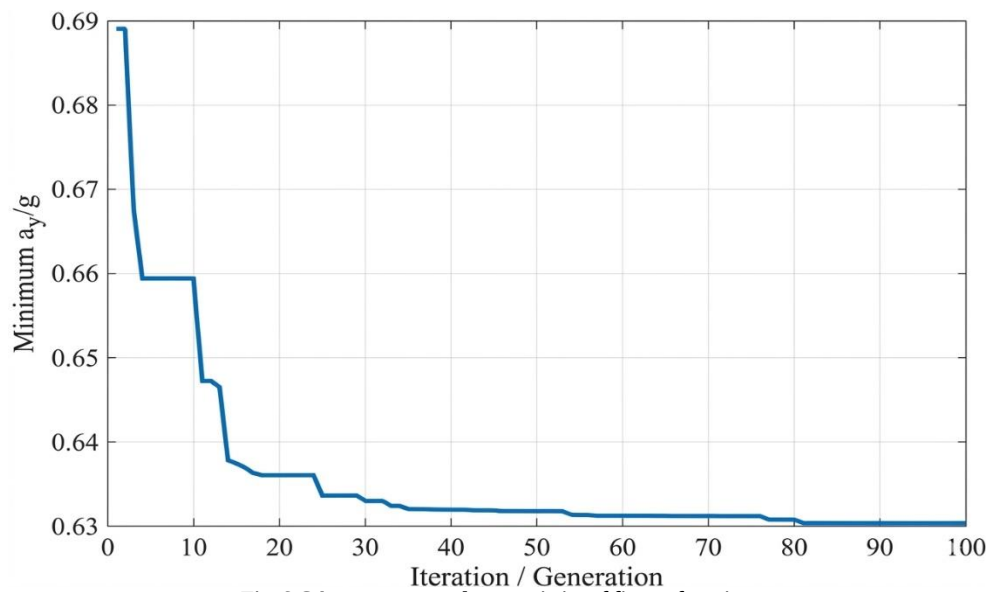


Fig. 6 GA convergence characteristics of fitness function

Table 2. GA optimized design variables

Parameters	Optimal Solution
t	1.5500 m
h	0.7500 m
h_r	0.1508 m
R_ϕ	0.8000 radians/g*

*1g=9.81m/s²

4.3. SFLA vs GA Optimisation

Table 3 presents the comparison of results of SFLA and GA.

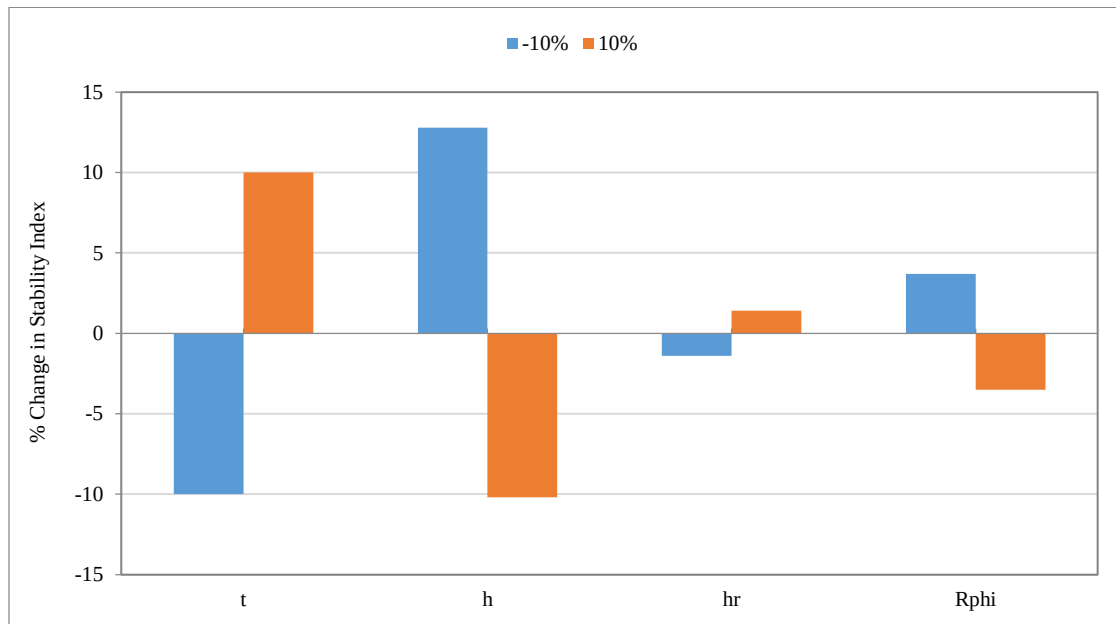
Table 3. Results comparison of SFLA and GA optimization

Aspect	SFLA	GA
Convergence	Smooth	Fast
Solution	Balanced	Extreme
Practicality	High	Moderate
Exploration	Moderate	Aggressive

Although the GA has achieved a lower objective function value, it has converged to boundary solutions, indicating aggressive exploitation of the search space and hitting the boundaries ($h=0.75$). In contrast, the SFLA has produced smoother convergence and has yielded balanced parameter combinations, which are more consistent with practical vehicle design considerations. Based on the SFLA and GA aspects comparison, since SFLA yields consistent results, it was decided to perform the sensitivity analysis for the SFLA-derived optimised design parameters.

5. Sensitivity Analysis

The SFLA-derived optimal parameters are subjected to local sensitivity analysis to narrow down the dominant parameters which govern the lateral stability. Each parameter is perturbed by $\pm 10\%$, and the percentage change in the fitness function (5) observed. The results of the sensitivity analysis is presented in Figure 7 and quantified in Table 4.

**Fig. 7 Change in stability index for design parameters perturbation ($\pm 10\%$)****Table 4. Results of sensitivity analysis**

Parameters	Sensitivity (% change in objective)	Sensitivity	Dominance in control
t	-10% = -10.00%, +10% = 10.00%	~10%	High
h	-10% = 12.83%, +10% = -10.21%	~11–13%	Highest
h_r	-10% = -1.35%, +10% = 1.39%	~1%	Lowest
R_ϕ	-10% = 3.74%, +10% = -3.48%	~3-4%	Low

Results interpret that the track width poses linear sensitivity, meaning a wider track width facilitates better rollover resistance. But this is a factor which is decided during the design phase, and it cannot be modulated in real-time. The roll rate and roll centre height are less dominant parameters with sensitivity magnitudes of ~3-4% and ~1%, respectively, posing a weaker influence.

The CG height is the most sensitive factor; by lowering it (-10%), it improves the stability by +12.83%, and by increasing it (+10%), it degrades the stability by -10.21%. So, of the lateral acceleration governing factors, the CG height is the dominating parameter and is chosen to be modulated in real-time for enhancing the lateral stability of an EV.

6. Active Height Control (AHC)

Corner rollover, or tipping sideways, happens during high-speed turning, evasive manoeuvres, or sharp corners when lateral acceleration becomes too high, causing a vehicle's Centre of Gravity (CG) to shift heavily toward the outside wheels [6, 11, 12].

Active Height Control (AHC) systems mitigate this risk by actively reducing the body roll angle and adjusting the vehicle's height to maintain stability [13-15], [40, 41, 45]. AHC systems often work in conjunction with Electronic Stability Control (ESC) or Roll-Over Mitigation (ROM) systems [21, 25 - 27]. The AHC system uses sensors (lateral

acceleration, vehicle speed, and suspension height) to detect imminent rollovers and adjusts the hydraulic pressure in the shock absorbers to stiffen the suspension on the outside of the turn and soften the inside [28, 29].

This action directly counters body lean and keeps the vehicle flatter [31-33]. In the proposed work, it is postulated that the electro-hydraulic valve, which adjusts the hydraulic pressure, can be commanded by deriving the control signal by comparing the SFLA-optimised CG height against the LVDT-measured actual in the ECU [50]. The outcome is to actively adjust the CG height in real-time to mitigate the tendency of rollover during a vehicle negotiating a corner.

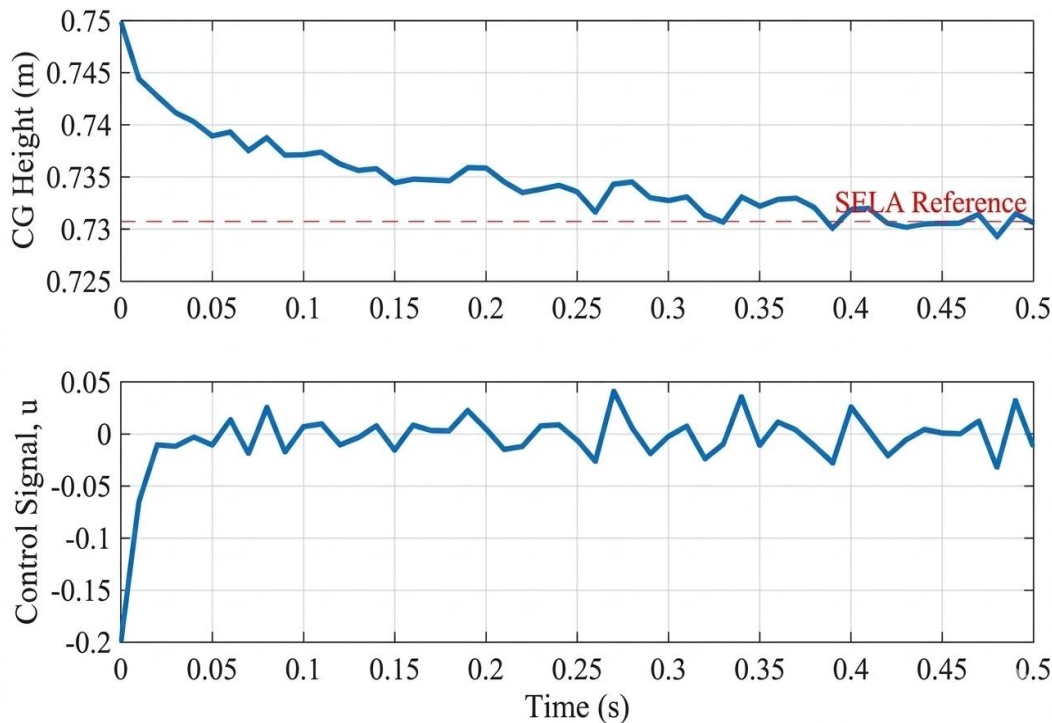


Fig. 8 The CG height modulated by PD control signal for AHC to follow the SFLA reference

Figure 8 presents the CG height being modulated by the Proportional Derivative (PD) control signal to follow the SFLA reference. The initial CG height was declared as 0.8 m in the coding, which is an unsafe condition. The controller gains, proportional and derivative, are tuned to 2.0 and 0.2, respectively. The time constant for the actuator dynamics is assumed to be 0.1 s. It is evident from the simulation results that the AHC effectively modulates to SFLA reference within 0.25 s. The trade-off of this PD control method is the electro-hydraulic valve's continuous activation for the noises picked up by the sensing elements and the signal conditioning circuits. To alleviate this, the Model Predictive Control (MPC) is experimented with. MPC is an advanced control strategy that optimises system behaviour by predicting future outputs over a finite horizon using a dynamic model of the plant. At each sampling instant, MPC solves a constrained optimisation problem to compute the control inputs that minimise a

predefined cost function, typically balancing tracking performance and control effort, while explicitly handling system and actuator constraints. Only the first control action is implemented, and the process is repeated in a receding horizon manner, enabling real-time adaptation to disturbances and model uncertainties. This capability makes MPC a suitable one for the complex and multivariable systems, such as the electric vehicle AHC [20, 22]. An offset-free MPC method is adopted in this work, which features the addition of disturbances in the system dynamics which mimic the real-world on-road scenarios. This method assures zero steady-state error in CG height regulation. It also enhances the robustness under varying driving conditions, which are the necessary requirement in MPC-based AHC [9, 10]. Figure 9 presents the MPC output and SFLA reference CG height follow-up for active rollover mitigation. Section 6.1 details the parameterisation.

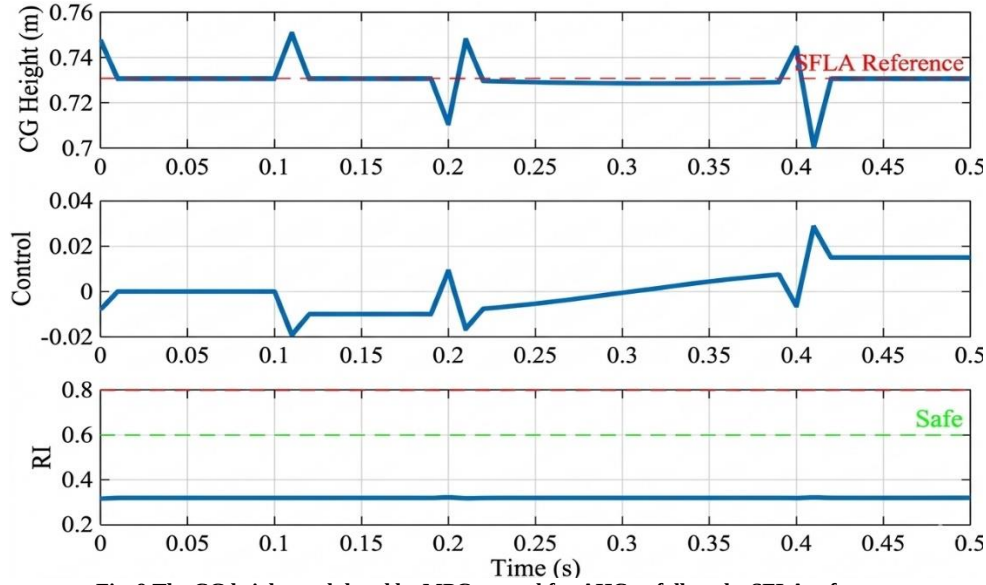


Fig. 9 The CG height modulated by MPC control for AHC to follow the SFLA reference

6.1. MPC Parameterisation

Table 5. MPC parameterization

Mathematical Parameters	MPC formulation Values
Sampling time (dt)	0.01 s
Prediction horizon (N_p)	25 samples
Control horizon (N_c)	8 samples
Output weight matrix (Q)	$300I_{25}$
Control weight matrix (R)	$0.01I_8$

For the implementation of the MPC, the parameterisation adopted is presented in Table 5. The relatively high value and low value weight assignments for the output and control matrices, respectively, demonstrate fast tracking of the SFLA-derived optimal CG height and controller to enable stringent control.

The AHC system is modelled as a first-order discrete-time state-space model and is incorporated with a constant as well as slowly varying disturbance state to facilitate off-set free tracking as presented in Equation (10). The output is modelled as presented in Equation (11).

$$x(k+1) = Ax(k) + Bu(k) + d(k) \quad (10)$$

$$y(k) = Cx(k) \quad (11)$$

Where $x(k)$, $u(k)$ and $d(k)$ are the controlled variable defined as the CG-height deviation from reference, AHC actuator control input and the unknown external disturbance respectively. From the parameterisation presented in Table 5, the discrete-time state matrices are $A = [0.9]$, $B = [2]$ and $C = [1]$. In the simulation, three disturbance conditions (step changes, $d(k) = 0.02$, change in direction, $d(k) = -0.03$ and time-varying disturbances, $d(k) = 0.02\sin(10t)$ are adopted to emulate real-world vehicular scenarios. The results

presented in Figures 8 and 9 demonstrate the effectiveness of the proposed method in regulating the vehicle's CG height. The MPF is fed with the reference and actual CG height, the former derived from SFLA (0.7307 m) and the latter through LVDT sensing technology (assumed as 0.8 m in simulation).

The MPC commands the electro-hydraulic valve of AHC to accurately modulate the CG height to the SFLA-derived optimal reference. It is evident from Figure 9 that the control signal remains smooth and bounded, indicating stable actuator behaviour. It is also evident that the Rollover Index (RI) stays well within the safety threshold of 0.6. This confirms that the vehicle operates within a safe stability margin. These results validate that the integration of metaheuristic optimisation with MPC for AHC enables robust CG height regulation and effective mitigation of rollover risk in EVs.

7. Experimental Demonstration

Figure 10 presents an LVDT with a metric micrometre, an associated signal conditioning circuit, and a servo motor positioning system to demonstrate the functioning of an electro-hydraulic valve to control the volume of fluid flow to modulate the suspension pressure and, hence, the modulation of the CG height to mitigate rollover risk. Figure 11 presents the LVDT with a metric micrometre, which is considered to emulate sensing of the actual CG height of the vehicle.

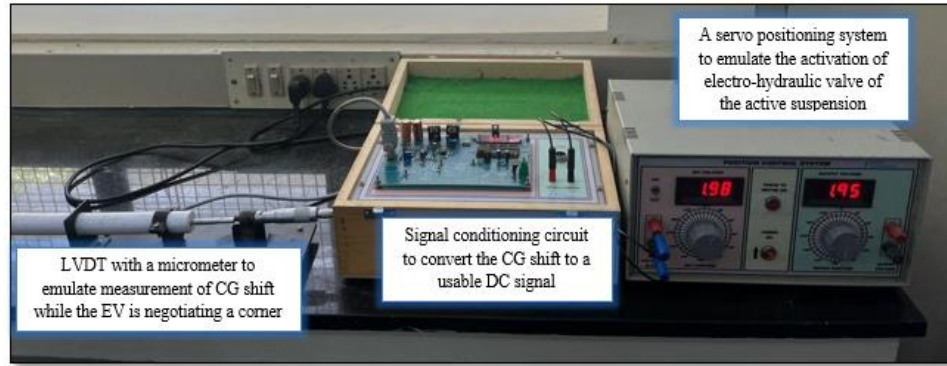


Fig. 10 The experimental setup to demonstrate the CG variation and corresponding electro-hydraulic valve servo positioning

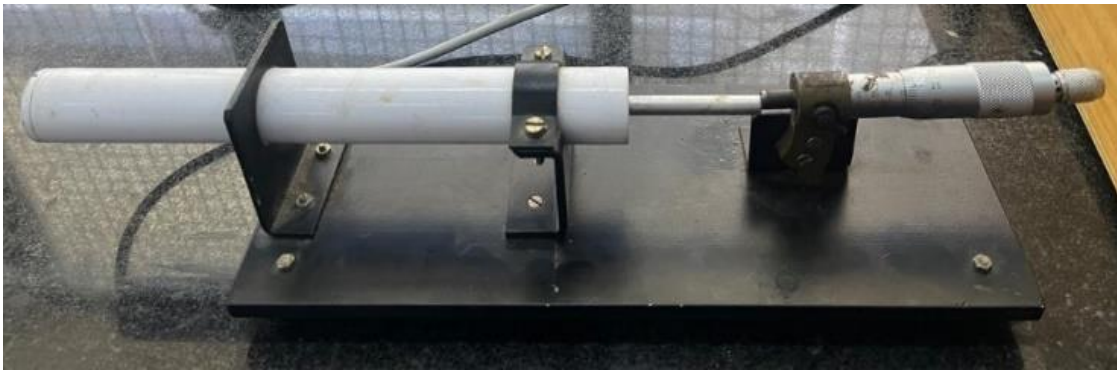


Fig. 11 LVDT with a metric micrometer

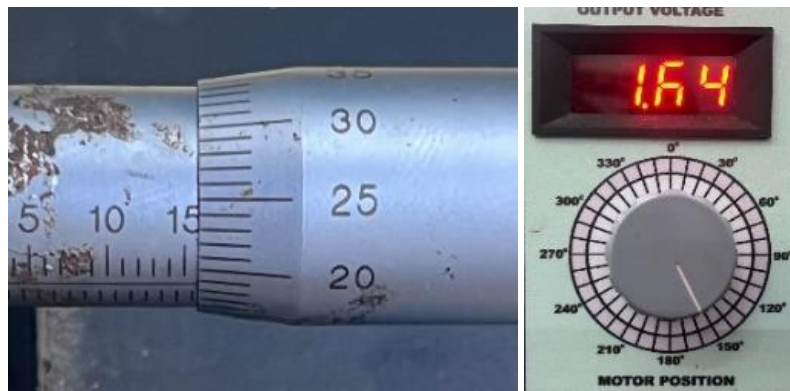


Fig. 12 Initial displacement is fixed at 15.69 mm, considered as the conditions for the reference CG height

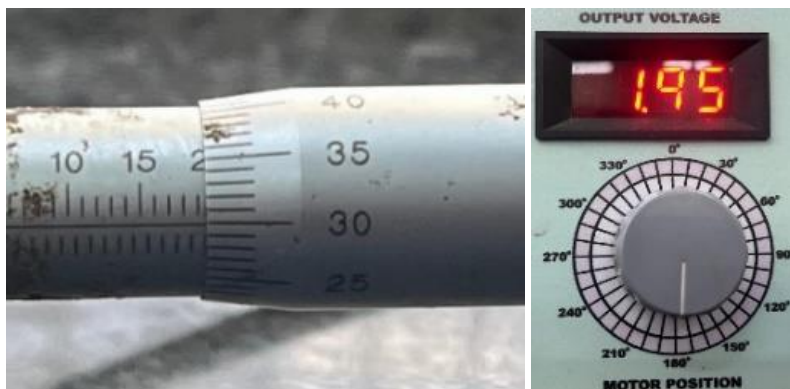


Fig. 13 The displacement fixed at 19.80 mm, considered as the condition for deviation of CG height during a cornering manoeuvre

Table 6. Non-dimensional scaling factors mapping benchtop test to full-size EV dynamics

Parameters	Absolute scaling range w.r.t benchtop test	Normalized non-dimensional Value	Scaling factor mapping benchtop test to full-size EV dynamics
Full-Scale EV CG Position (X)	0.80 m to 0.7307 m	0.0875	-
Tabletop Micrometer (x)	15.69 mm to 19.80 mm	0.2620	Kinematic scaling (X/x) = 0.334 m/mm
LVDT Output Voltage (V)	1.64 V to 1.95 V	0.1890	-
Servo Actuator Angle (θ)	153 degrees to 175 degrees	0.1438	Control scaling (V/θ) = 0.761 degrees/volt

Figure 12 presents initial displacement fixed at 15.69 mm and the corresponding signal output to be 1.64 V, for which the position of the servo valve is 153 degrees. This can be considered the conditions for the reference CG height. Considering a CG displacement of 4.11 mm in real-time, with the micrometre reading 19.80 mm, the corresponding signal output from the LVDT is 1.95 V, for which the position of the servo valve is 175 degrees, which is shown in Figure 13. This can be considered the conditions for the actual CG height and the servo valve's response to follow the reference CG height.

To ascertain CG shift to the SFLA reference, the scaling ratio linking the micrometer and servo positioning are a sensor sensitivity of 0.0754 V/mm and actuator sensitivity of -3.1818 mm/degree.

Table 6 presents the non-dimensional scaling factors mapping benchtop test to full-size EV dynamics. The non-dimensional operating states are defined by normalising parameters against their baseline equilibrium conditions. The scaling factor mapping the benchtop test to full-size EV dynamics are 0.334 m/mm (CG shift to micrometer displacement) and 0.761 degrees/volt (servo actuator angle to LVDT analog signal) which are the kinematic and control scaling respectively.

This demonstration proves a methodology for measurement of CG height in real-time and modulate the servo valve to facilitate allowing hydraulic fluid to flow from the high-pressure suspension circuit back to the lower-pressure reservoir or tank or vice versa to closely track and maintain the CG height at the SFLA reference, mitigating rollover events.

8. Study Limitations and Future Research Directions

8.1. Study Limitations

A quasi-steady roll plane analysis is proposed, assuming the vehicle dynamics are in a continuous sequence of steady states, which is not the real-world scenario when a vehicle is negotiating a corner. Further, the practical implications of the proposed methodology are limited to experimental demonstration of CG shift sensing (LVDT) and corresponding

electro-hydraulic valve positioning (Servo). The proposed work is constrained to lateral acceleration optimisation, considering only the modulation of the CG height parameter.

8.2. Future Research Directions

As a future research direction, the proposed method can be extended to more complex vehicle models considering the vehicle dynamics, focusing on tyre-road interactions and nonlinear suspension behaviours. The presented experimental demonstration can be extended to actual vehicular infrastructures to validate the proposed method in real-time.

The other metaheuristic methods for non-linear optimisation problems can be compared and contrasted for the proposed methodology. Adaptive MPC and reinforcement learning-based controllers based on real sensor data can be developed to enhance performance under highly uncertain environments. The proposed methodology can also be extended to multi-objective optimisation, considering additional design parameters and performance metrics such as ride comfort, energy efficiency, and passenger safety.

9. Conclusion

In this work, a methodology for enhancing the lateral stability of electric vehicles using a metaheuristic optimisation approach with an MPC-based AHC system is proposed. SFLA is used to optimise the vehicle parameters influencing lateral acceleration. The optimised parameters are benchmarked against GA to prove the performance of SFLA. The dominating parameter which governs the rollover risk is narrowed down using local sensitivity analysis and used as input to the MPC. In the simulation, the SFLA-optimised CG height of 0.73 m is fed as reference input to the constrained MPC system, and the initial CG height is declared as 0.8 m, which is an unsafe condition. The control signals are generated from the MPC, which can be fed to the electro-hydraulic valve to modulate the pressure in the hydraulic suspension system, and hence, the AHC is presented. The simulation results show effective tracking of SFLA reference, and a rollover index of 0.33 against the threshold value of 0.6 ensures enhanced vehicle stability. Furthermore, an experimental demonstration is presented to show the avenues of measurement of CG height of a vehicle using LVDT. An associated signal conditioning

circuit and activation of the electro-hydro valve using a servo motor to emulate the AHC hydraulic suspension system are also presented.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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