Cost Function Reduction Using Stability-Informed Bayesian Optimization for the Model Predictive Control of a Semi-Active Suspension System

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ABSTRACT

Traditional Model Predictive Control (MPC) performance is very sensitive to the state-weighting matrix *Q* and the control-weighting *R*, resulting in time-consuming and suboptimal results. This work introduces a smart control approach for semi-active suspension systems that combines MPC with Stability-informed Bayesian Optimization (SiBO). The Bayesian framework uses a neural network surrogate model to approximate the cost function, significantly reducing the number of iterations required for optimization. Using a quarter-car model with a Magnetorheological (MR) damper, the method tackles the challenge of non-linear damping by linearizing it and directly integrating it into the MPC cost function. This reduces the computational load and makes the control more suitable for real-time use. The proposed strategy optimizes the damping coefficient to balance ride comfort and stability. Compared to traditional methods, it delivers clear improvements. The system showed a 15% reduction in Root Mean Square (RMS) body acceleration and a 12% improvement in suspension travel over standard Proportional–Integral–Derivative (PID)-tuned damping. It also achieved faster convergence, reaching optimal performance in just 10 iterations. In contrast, Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) required more than 50 iterations to reach such results.

Keywords-semi-active suspension; Model Predictive Control (MPC); cost function reduction; Bayesian Optimization (BO); ride comfort; vehicle stability

I. INTRODUCTION

Suspension systems have a significant impact on vehicle performance, as they directly affect ride comfort, safety, and stability. Depending on how they generate control forces, suspensions are categorized as passive, active, semi-active, and energy feedback systems [1]. A semi-active suspension system actively modifies its damping properties in response to changing road conditions and vehicle dynamics by employing control mechanisms that maximize ride quality. These systems provide a balance between traditional passive suspensions and fully active systems, optimizing both ride comfort and handling [2].

Several types of semi-active suspension systems have been developed, differentiated by their control mechanisms and the technologies used to adjust damping characteristics to suit road conditions. One widely used approach employs Magnetorheological (MR) dampers, where the suspension characteristics are controlled using an electromagnet. The electromagnet regulates the suspension properties, dynamically modifying the fluid's viscosity. Increasing the current through the electromagnet aligns the metallic particles, raising fluid viscosity and, consequently, the damping effect. Conversely, lowering the current decreases viscosity, resulting in a softer damping response [2].

A suitable controller must be used to obtain the most effective damping coefficient for the MR dampers. Researchers have extensively investigated numerous control algorithms, such as fuzzy logic, neuro-fuzzy, sliding mode, skyhook, groundhook, linear quadratic regulator (LQR), and linear quadratic Gaussian controllers. The skyhook control approach [3], initially presented in 1974, was thoroughly tested to enhance ride comfort and reduce vibration levels by adjusting spring stiffness. However, this approach slowed the system response and did not yield optimal performance [4]. As a result, a LQR was implemented in a quarter-car model [5] to improve both handling and ride comfort. The main challenge, however, was the need to continuously specify the exact state values of the suspension links [6].

Sliding mode control has also been widely explored for suspension systems, showing robust and efficient performance under uncertainties. However, once the controller enters the sliding phase, it becomes less sensitive to changes in plant characteristics and inputs [7]. Because of the inherent nonlinearity and complexity of suspension systems, accurately assigning the damping coefficient remains challenging. Fuzzy logic techniques provide an alternative by enabling damping coefficient assignment without requiring a precise mathematical model [8]. For certain road excitations, a well-designed rule base can yield satisfactory damping performance [9].

To further improve performance, Artificial Neural Network (ANN) controllers have been combined with conventional controllers. Data from conventional control studies are used to train ANN controllers [10]. Moreover, ANN controllers have been applied under abnormal conditions, such as damper aging and degradation, where the system maintained good performance by accounting for its current state [11].

Model predictive control (MPC) represents another effective approach for vehicle suspension control. MPC has been applied in a variety of forms, including cloud-based MPC [12], neural network-based MPC [13], stochastic MPC [14], preview-control MPC [15, 16], hybrid optimal MPC [17], and fault-tolerant MPC [18]. The cost function formulation is critical to the MPC framework, as it balances control objectives and trade-offs between conflicting performance criteria. Dissipativity constrains, which control the energy dissipation characteristics of the dampers and influence suspension effectiveness, complicate the cost function design while preserving performance objectives [19]. Typically, a quadratic cost function representing predicted system states and control inputs over a specified prediction horizon is minimized [20, 21].

Cost function reduction can be achieved by optimizing its formulation, linearizing nonlinear functions to lower computational load, considering mechanical constraints in the MPC design, and using preview road information to predict future disturbances and improve control inputs. In this paper, we present cost function optimization using a neural network within the MPC framework. A mathematical model of a quarter-car system with a semi-active suspension is considered [22].

II. QUARTER-CAR SYSTEM MODELING

The semi-active suspension system of a quarter-car model with two degrees of freedom is considered, as illustrated in Figure 1. The quarter-car model simplifies the vehicle to a single wheel and its associated suspension system. Here, ms represents the sprung mass supported by the suspension, mu denotes the unsprung mass of the wheel and other components not supported by the suspension, and ks indicates the suspension spring stiffness. The tire is modeled as a spring with stiffness kt, cs is the damping coefficient of the damper, zs is the displacement of the sprung mass, zu is the displacement of the unsprung mass, and zr is the road displacement input caused by surface irregularities.

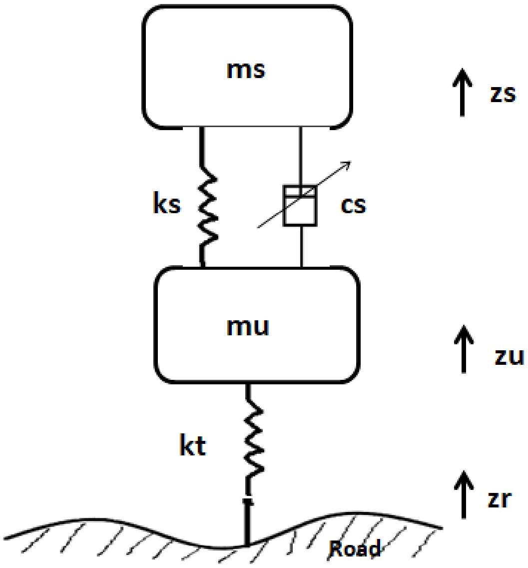

Fig. 1. Model of the quarter-car semi-active suspension system.

The system equations for the model are given by:

$$ms.\ddot{zs} + cs(\dot{zs} - \dot{zu}) + ks(zs - zu) + u(t) = 0 \tag{1}$$

$$mu.\ddot{zu} + cs(\dot{zu} - \dot{zs}) + ks(zu - zs) + kt(zu - zr) = u(t) \tag{2}$$

The vehicle experiences random excitations from uneven road surfaces. The suspension system is designed to absorb energy and reduce the vibrations induced by these excitations. For optimum ride comfort, the spring stiffness must be adjusted, or the damping coefficient controlled. The semi-active suspension system dynamically modifies the damping characteristics in response to vehicle dynamics and changing road conditions. Control strategies are therefore crucial to optimize vehicle performance, improve ride comfort, and enhance stability. MPC is one of the most promising modern control strategies for managing such dynamic systems effectively.

III. COST FUNCTION OPTIMIZATION IN MODEL PREDICTIVE CONTROL

MPC uses an optimization-based framework to efficiently manage dynamic systems. To forecast future behavior and make well-informed control decisions, it uses a mathematical model of the system. The cost function, which quantitatively expresses the goals of the control task, is one of the essential elements of MPC. Achieving the intended performance in a variety of applications, including industrial processes, depends on the design and optimization of this cost function. Some of the ways to reduce the cost function are:

- Optimize cost function formulation: Formulate the cost function as efficiently as possible by carefully weighting the trade-offs between handling performance, energy consumption, and ride comfort. To achieve the desired performance, provide appropriate weights to parameters such as sprung mass acceleration, suspension deflection, and control effort.
- Linearization and simplification: To lower the computational burden and reduce the cost function, linearize the non-linear damping forces, making the optimization problem easier to handle and solve more quickly.
- Constraint handling: The mechanical limitations of the suspension system should be accounted for in the formulation so that the controller can avoid unnecessary calculations and focus on identifying the best solution within practical constraints by specifying feasible regions for the control inputs.
- Road preview information: Use preview road information to anticipate future disturbances and adjust the control inputs accordingly. This enhances overall performance and reduces the cost function by enabling the controller to predict and mitigate the effects of road irregularities in advance.

Ways to reduce the delay in reaching the optimum value in a semi-active suspension system using MPC include:

- Shift delay compensation: Implement a prediction system that operates independently of the MPC to compensate for the shift delays arising from the actuators. This can decrease the time required to attain the optimal control input and produce more accurate suspension velocity predictions.
- Improved Smith predictive control: Use an improved Smith predictive time-delay compensation controller, such as one combined with a fuzzy controller. This can effectively solve the time-delay dynamic compensation problems and improve the system's robustness to delays.
- Observer-based approach: Use an observer to estimate the information about road disturbances so that the controller can use it in the prediction step. This can shorten the time required to reach the optimal value by improving the controller's capacity to react to disturbances more rapidly and precisely.
- Algorithm optimization: Reduce computational complexity and speed up MPC execution by optimizing the algorithm itself. This may involve using parallel processing, effective numerical solvers, or simplifying the prediction model without sacrificing accuracy.
- Hardware improvements: Employ more efficient sensors and faster processors to minimize delays in implementing control actions.

The computational load of MPC is frequently criticized, especially in real-time applications. Advanced techniques are used to reduce this load, such as removing unnecessary constraints that have no bearing on the optimization result, freeing the controller to focus on a smaller number of constraints. This reduction allows MPC to function effectively in complex dynamic contexts, resulting in more efficient computation. The optimization algorithm plays a crucial role in enhancing ride comfort and vehicle stability. Several optimization methods, including Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), fuzzy logic, etc., have been explored for this purpose, each contributing unique advantages [23-26].

Despite frequently requiring significant processing resources, GAs are suitable for optimizing mechanical parameters in automobiles because they use the principles of natural selection to evolve solutions across generations. PSO, on the other hand, shows fast convergence and effectiveness in determining the optimal parameters for dynamic systems by iteratively updating a population of potential positions based on individual and collective experience.

By combining Stability-informed Bayesian Optimization (SiBO) with MPC [27, 28], this study presents a strategy that simultaneously addresses multiple competing objectives, enhancing ride quality and overall vehicle stability. Unlike more conventional approaches like GA and PSO, this strategy successfully integrates optimization and control techniques to adjust dynamically to changes in load situations. This method leverages the predictive capabilities of MPC, which can forecast future output trends based on historical and current data. By maximizing control variables across a receding horizon, the performance index in SiBO is minimized, ensuring that the controller can efficiently react to impending disturbances.

In this context, neural networks have become highly effective tools for cost function optimization. They are particularly well-suited to managing the complexities of dynamic systems and adapting to real-time changes in operating conditions because of their ability to model intricate non-linear interactions.

IV. CONTROL METHODOLOGY

An MPC controller is designed to regulate suspension performance by minimizing body acceleration and suspension deflection. Figure 2 shows the block schematic of the control strategy. By forecasting future states and control inputs, the MPC controller selects the control actions that minimize the quadratic cost function. Based on stability-informed criteria, the damping coefficient parameters are iteratively updated using Bayesian Optimization (BO) to minimize this cost function. BO efficiently directs the search toward the optimal damping values by approximating the cost function using a Gaussian process or a neural network surrogate. Thus, the MPC + BO strategy minimizes the overall cost function, accounting for both ride comfort and stability while ensuring that the system dynamically adjusts to road conditions.

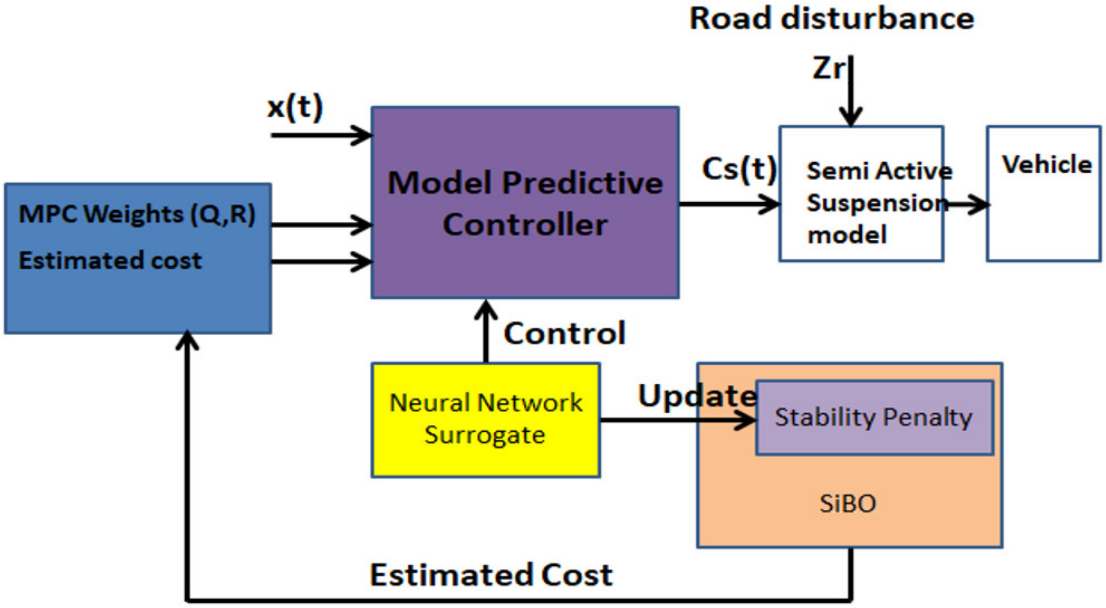

Fig. 2. Block diagram representation of MPC with SiBO.

The flowchart in Figure 3 illustrates the optimization loop for the MPC + BO approach. Within this framework, neural networks serve as highly effective tools for cost function optimization, as they can model intricate nonlinear interactions and adapt to real-time changes in operating conditions.

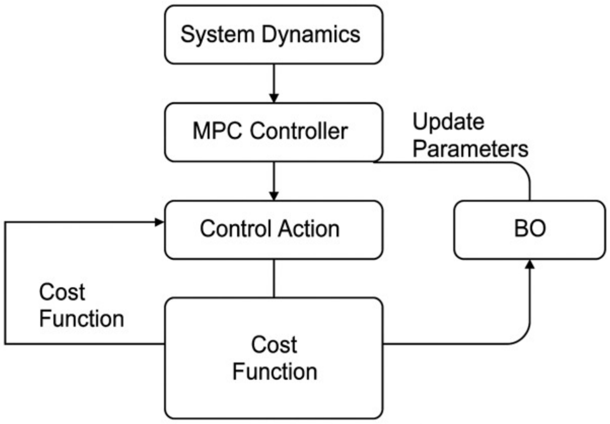

Fig. 3. Flowchart of the optimization loop for the MPC + BO approach.

The state-space representation of the quarter-car model is given as follows. The system states include suspension deflection ($zs - zu$), sprung mass velocity ($\dot{zs}$), tire deflection ($zu - zr$), and unsprung mass velocity ($\dot{zu}$). Therefore, the state can be expressed as:

$$x(t) = [\,zs - zu \quad \dot{zs} \quad zu - zr \quad \dot{zu}\,]^T \qquad (3)$$

The continuous-time state-space form of the quarter-car model is given by (4) and (5):

$$\dot{x}(t) = A.x(t) + B.u(t) \qquad (4)$$

$$y(t) = C.x(t) \qquad (5)$$

where $y(t)$ is the output, including the suspension deflection ($zs - zu$) and the sprung mass acceleration ($\ddot{zs}$), and $u(t)$ represents the road disturbance zr. The model is discretized with a sample time of Ts. The MPC is designed to control the damping force within the specified constraints cs_min and cs_max. The state matrices A, B, C of the modified system are:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -ks/ms & -cs\_min/ms & ks/ms & cs\_min/ms \\ 0 & 0 & 0 & 1 \\ ks/mu & cs\_min/mu & -(ks+kt)/mu & -cs\_min/mu \end{bmatrix}$$

$$, B = \begin{bmatrix} 0 \\ \frac{1}{ms} \\ 0 \\ -\frac{1}{mu} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

The standard cost function J for semi-active suspension is expressed as:

$$J(Q,R) = \sum_{k=0}^{N-1}\big((x(k) - xref(k)^T\, Q\, (x(k) - xref(k)) + u(k)^T R.u(k)\big) \qquad (6)$$

where $x(k)$ is the system state, $xref(k)$ is the reference (usually set to 0), $u(k)$ is the control input, and N is the prediction horizon. Q is the state-weighting matrix that penalizes deviations of system states (such as suspension deflection and body acceleration) from their reference values, and R is the control-weighting matrix that penalizes the control effort, in this case the damping coefficient. Both Q and R are automatically tuned using BO to achieve the desired trade-off between ride comfort, suspension travel, and system stability. The BO aims to minimize the cost function by evaluating the different (Q, R) pairs using a surrogate model.

BO does not inherently know whether a selected (Q, R) will cause instability. To address this, a stability penalty is added to the cost function to eliminate unstable controller configurations. It ensures that the BO prioritizes stable regions. The stability penalty term is defined as:

$$StabilityPenalty(Q,R) = \begin{cases} 0, & if\ stable \\ 10^6, & if\ unstable \end{cases} \quad (7)$$

The control objective is to determine the optimal time-varying damping coefficient $cs(t)$ to achieve optimal ride comfort (minimized body acceleration) and minimal suspension travel while ensuring system stability. The MPC tuned via BO minimizes the Root Mean Square (RMS) of the acceleration:

$$Jperf(Q,R) = \sqrt{\frac{1}{T}\int_0^T ((\ddot{z}s))^2\, dt} \quad (8)$$

The overall cost function $Jtotal$, inclusive of the stability penalty, is:

$$\begin{aligned} Jtotal\,(Q,R) = Jperf(Q,R) + \\ StabilityPenalty(Q,R) \end{aligned} \quad (9)$$

This framework allows the MPC controller to adaptively update control inputs based on the optimized Q, R values, ensuring improved ride comfort and system stability in real-time operation.

V. SIMULATION RESULTS

The quarter-car model comprises a sprung mass (ms = 350 kg) and an unsprung mass (mu = 40 kg) connected via a spring (ks = 18,000 N/m) and a semi-active damper. The wheel connects to the road through a tire modeled as a spring (kt = 195,000 N/m). The Simulink model of the plant is created based on (1) and (2). The displacements and velocities are the states, and the controllable damping force is the input. Initial values of Q and R are provided to the MPC framework. The neural network surrogate learns Q and R and the optimizer searches for the new Q and R values such that the closed-loop stability is maintained. The simulation was conducted over a 10 s time frame with a sample time of 0.001 s. The BO loop was executed for 10 iterations. The actuator constraints that form the input $u(k)$, which is the damping coefficient, are chosen as follows: $cs\_min \leq cs \leq cs\_max$, where cs_min = 100 Ns/m and cs_max = 900 Ns/m. These values are chosen from the standard range available for MR dampers.

The system exhibited a 15% reduction in RMS body acceleration and a 12% improvement in suspension travel compared to standard Proportional–Integral–Derivative (PID)-tuned damping, demonstrating the effectiveness of the proposed MPC with SiBO strategy in enhancing both ride comfort and vehicle stability. The neural network surrogate achieved a mean-squared prediction error of less than 0.01, ensuring that the cost function approximations within the parameter search space were highly accurate and reliable, thereby reducing the computational effort required for direct simulations.

The convergence of the optimization loop is illustrated in Figure 4, which shows that the cost function rapidly reaches its minimum within a few iterations, highlighting the efficiency of the BO framework. Figure 5 presents the variation of body acceleration over time, reflecting ride comfort performance, whereas Figure 6 shows the corresponding suspension travel over time, providing insight into the system's stability and damping behavior. Additionally, the Fast Fourier Transform (FFT) of the body acceleration for different Q and R weighting matrix values is shown in Figure 7. From Figures 5, 6, and 7, it is evident that the combination Q = 50 and R= 5 provides the optimal balance between comfort and stability, minimizing body acceleration while keeping suspension travel within acceptable limits.

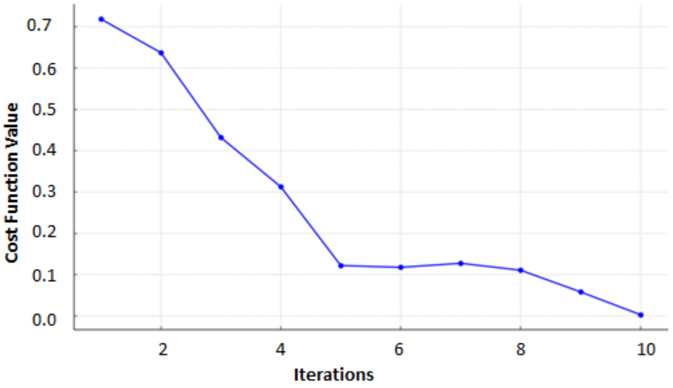

Fig. 4. Convergence of the MPC + BO optimization loop.

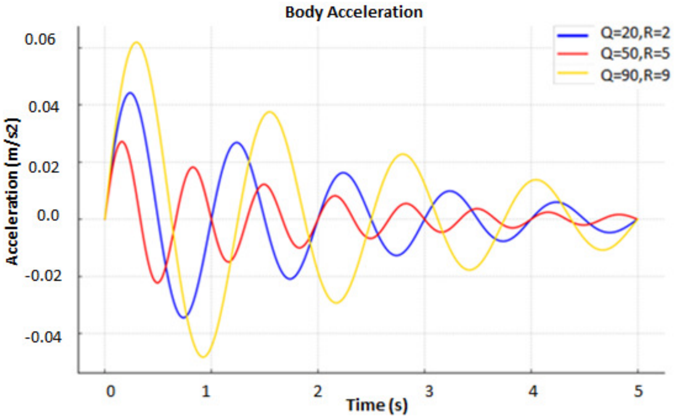

Fig. 5. Ride comfort: body acceleration over time for the quarter-car model.

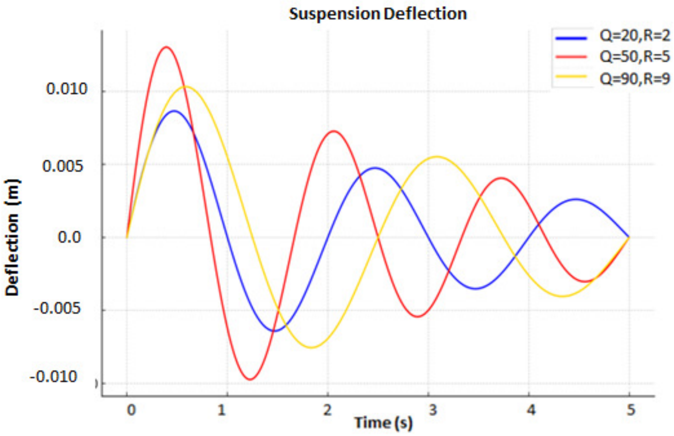

Fig. 6. Suspension travel over time for the quarter-car model.

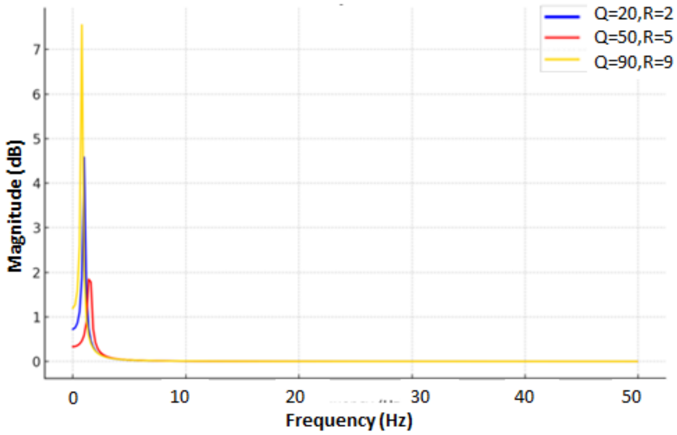

Fig. 7. FFT of body acceleration for different Q and R values.

Furthermore, the dynamic response of the suspension system to a 5 cm road bump at a vehicle speed of 20km/h is illustrated in Figure 8.

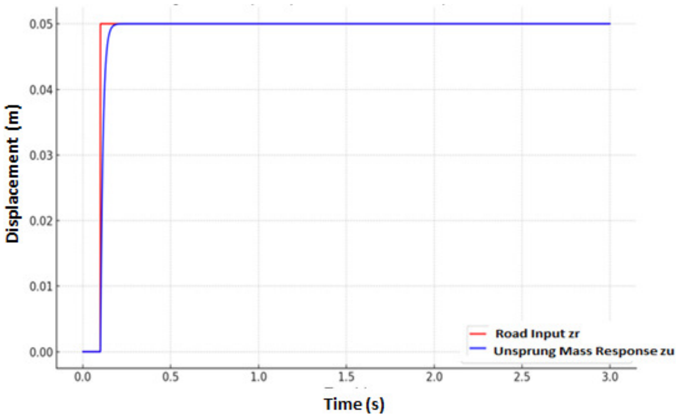

Fig. 8. Body displacement for a 5 cm bump at 20 km/h.

For a sinusoidal input, the system response is shown in Figure 9, and Figure 10 shows the comparison between different algorithms (PSO, PID) and the proposed method for a 10 cm pothole encountered at 20 km/h.

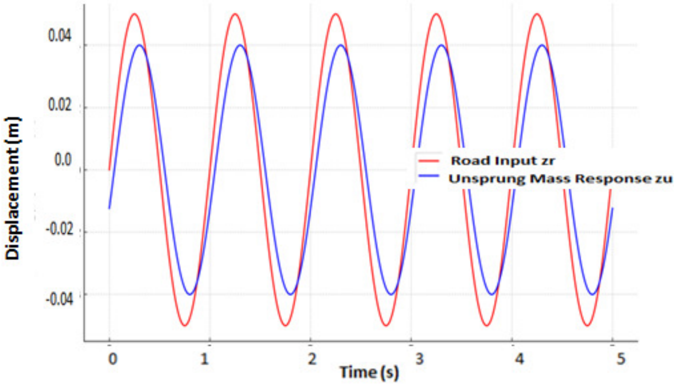

Fig. 9. Body displacement for sinusoidal road input.

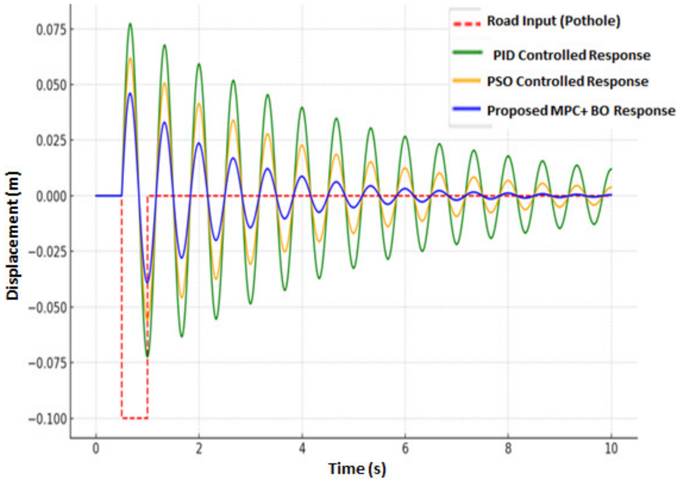

Fig. 10. Comparison of body displacement for a 10 cm pothole at 20 km/h across different control methods.

Table I presents a comparison of the performance between PID tuning, GA, PSO and the proposed MPC + BO method. It is evident from the results that the proposed MPC + BO approach not only reduces the number of iterations required for convergence, but also improves key performance metrics, including suspension travel, unsprung mass displacement, and RMS body acceleration.

TABLE I. COMPARISON OF PERFORMANCE PARAMETERS OF DIFFERENT CONTROL METHODS

Method	RMS body acceleration (m/s^2)	Suspension travel (m)	Convergence iterations	Simulink evaluations	Remarks
PID tuning	2.85	0.043	Manual tuning	~20	High manual effort
GA optimization	2.61	0.039	55	55	Slower convergence
PSO optimization	2.58	0.038	50	50	Requires tweaking
Proposed MPC + BO	2.41	0.036	10	10	Fastest, most stable response

VI. CONCLUSION

This work introduces a hybrid control framework that combines Model Predictive Control (MPC) with Stability-informed Bayesian Optimization (SiBO), leveraging probabilistic optimization with stability constraints to ensure faster convergence and improved robustness compared to traditional tuning of the Q and R weighting matrices in the MPC cost function. By linearizing the inherently non-linear damping force and embedding it within the cost function, the computational burden is significantly reduced without compromising control performance. This enables the MPC to solve its optimization problem rapidly, making it well-suited for real-time implementation.

Compared to traditional optimization techniques such as Genetic Algorithms (GAs) and Particle Swarm Optimization

(PSO), the SiBO method demonstrated markedly faster convergence, requiring only 10 iterations versus over 50 for GAs and PSO. Moreover, by incorporating system dynamics directly into the cost function, the proposed approach achieved enhanced stability, an aspect often neglected by GAs and PSO.

The integration of a neural network surrogate further minimized the reliance on computationally intensive Simulink simulations at each iteration, thereby reducing overall computational cost. The system exhibited a 15% reduction in Root Mean Square (RMS) body acceleration and a 12% improvement in suspension travel compared to standard Proportional–Integral–Derivative (PID)-tuned damping.

By reducing iteration count and computational load, the proposed approach makes advanced MPC-based control feasible for real-time vehicle applications. Additionally, while conventional PID tuning offers simplicity, it lacks adaptability to varying road conditions and requires extensive manual intervention, underscoring the advantages of the proposed methodology.

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