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A hybrid metaheuristic control algorithm design for improved reliability of Adaptive Cruise Control System in Autonomous Vehicle

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Abstract –*The modern era vehicles generally have an Cruise Control (ACC) system installed in them. Intended to assist drivers, some researchers have worked on multi-objectives like road safety improvement and driving process enhancement; hence, approaches like Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC) are primarily used in the literature. As indicated in various literature, ACC equipped with MPC can be designed with multi-objectives and constraints for improved and reliable performance of automated vehicles. Therefore, ACC system based on MPC with an optimization known as Coati Optimization Algorithm (COA), i.e., MPC-COA, is introduced in this manuscript. The proposed COA for ACC provides necessary stability and maintains a safer distance between the ACC equipped host vehicle and the former target vehicle. The proposed MPC-COA technique is simulated on the MATLAB platform, and the results based on performance metrics like desired acceleration input, velocity error, distance error, and acceleration of ACC equipped host vehicle are compared with those of the conventional LQR and MPC controller. By this introduced strategy, the acceleration, the velocity, and the inter-vehicle distance error are regulated optimally. Consequently, the convergence speed is enhanced, and the optimal solution is maintained without deviation in the desired performances. The controller is further evaluated for different prediction horizons(N).*

Keywords – Adaptive Cruise Control, Automated Vehicle, Coati Optimization, Linear Quadratic Regulator, MPC-COA.

1. INTRODUCTION

Post COVID-19, vehicle automation plays a very crucial role in several aspects of transportation. It is still a work in progress, and there are several technical, regulatory, and societal challenges to be addressed before widespread deployment of automated vehicles is achieved. Technical reliability, safety, cybersecurity, legal frameworks, and public acceptance are among the factors that need to be considered and managed effectively as automation continues to evolve. In recent years, researchers have delved into a variety of literature to find the best methods for controlling ACC systems. The problems associated with the present techniques that have been implemented recently are listed in Table 1.Facilitating the driver based on Longitudinal Vehicle (LV) control is termed as Cruise Control (CC) [1]. Earlier model of CC equipped vehicles allowed the driver to maintain a specific pace while driving on highway [2]. An automated vehicle control system, Adaptive Cruise Control (ACC) is extensively implemented in modern vehicles which provides developed and smart driving solutions [3] as shown in Fig. 1. The major objective of the ACC is to maintain velocity of the LV by tracing the velocity as per driver's requisition. There is also an additional tracking of leading vehicle's velocity and adjusting to it, by accelerating the automobile autonomously [4]. Radar is used as an external sensor for measuring the distance between the two vehicles. The radar sensing system is also used to identify the relative velocities between the two vehicles. Vehicle dependent and independent parts are the two subsystems of the ACC. The required vehicle's acceleration and deceleration profile is measured by the former. By actuating the brake system and throttle, dependent part i.e. the controller part tracks the vehicle profile [5].

If there is no target vehicle, the speed on the predetermined rate is regulated by the host vehicle equipped with ACC system. However, the host vehicle spontaneously moves along with the target vehicle at an appropriate safe distance when a target vehicle is identified. Proportional Integral Derivative controllers have been proposed in [6] for maintaining a safe vehicle-following distance and also for regulating the inter-vehicular distance and relative vehicle velocity. In [7], self-tuning control algorithm for ACC is developed based on short time linear quadratic form estimation technique to track the vehicle's longitudinal dynamics for a safe ride. During the vehicle following process, collision may occur. In order to avoid collision, [8] suggested that a definite inter-distance is inhibited between host and target vehicle to maintain a non-collidable range. Moreover, for imitating drivers' safe vehicle-following behaviour, neural and fuzzy controllers have been implemented in [9], [10].

Driving comfort and safety is also an important considerable factor for safe vehicle-following. In[11], a

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survey report from National Highway Traffic Safety Administration highlights that driving comfort needs more improvement as owing to discomfort, few people refuse to use automated vehicles. ACC equipped commercial vehicles enhance passengers' comfort and minimizes the fuel consumption too. Generally, for estimating the discomfort handled by drivers, acceleration is an essential metric in the ACC's longitudinal control [10], [12]–[14] .

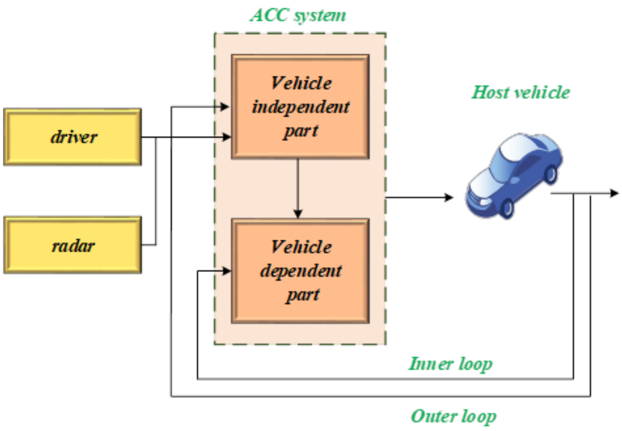

Fig. 1. Structure of ACC.

Table 1. Comparison of previous work.

Ref	Control strategy	Merits	Drawbacks
[15]	ACC	Safe platooning	Poor speed control
[16]	ACC	Higher braking effect	High error convergence
[17]	ACC	Vehicle safety	Limited speed control over longer distance
[18]	Discrete Hybrid MPC	Safe platooning	Computational complexity
[19]	CACC	Enhance string stability Response bandwidth	Real time implementation is difficult
[20]	Hierarchi -cal ACC	Tracks desired acceleration with elimination of vehicle crashing	Poor system performance
[21]	CACC	Balanced string stability	Weak numerical simulations

By restricting the values of acceleration and jerk, [22]–[24] developed a better comfort in ACC. The approaches like Model Predictive Control (MPC) and Linear Quadratic Regulator (LQR) are widely utilized in the literatures for ACC. Several existing techniques such as LQR in [9], [25] , provides driving safety and comfort by implementing ACC-based algorithms. Further, fast computation accomplishment was formulated with the help of MPC combined with several optimization solvers.

A compensation strategy based on time delay, stability and disturbance analysis for designing ACC system was elaborated in [15]. A system adopted technique was used for velocity-dependent spacing functions for stability improvement of ACC ,time lag in vehicle dynamics, actuators and different sensors in [16]. The system model was transformed into homogeneous structure without affecting the system dynamics. Based on

the multi-objective optimization and inertial-triggered mechanism, an ACC with high performance configuration was developed in [17].For achieving the efficient traffic system through Autonomous Vehicle (AV) platooning ,discrete hybrid stochastic MPC approach was determined in [18].Also, the future acceleration profile and current velocity profile of the following vehicle were obtained using mixed -integer programming technique.

The Cooperative ACC (CACC) was implemented on vehicles with different types of powertrains by developing hierarchical architecture framework in [19]. The dynamic constrained time gap trajectory planning algorithm was used for handling the vehicle gaps. A robust string stable CACC was enabled using the adopted technique. For the crash avoidance in various lanes, a hierarchical ACC was introduced in [20].The desired acceleration was tracked and the maximal longitudinal tire force was utilized by sliding mode control. The verification about the performance in real-time and effective working was handled by the Driver-in-the-Loop (DiL) platform for different scenarios. The stability of the string with CACC, ACC and human vehicles was compared in [21].Overall literature showed that the technical reliability and passenger's comfort are the two most important factors to be considered and managed efficiently as AV evolve.

To mitigate the various problems as stated in literature and in Table 1 in this manuscript, a hybrid metaheuristic MPC-COA based ACC control is implemented for satisfying multi-objectives. Dealing with the various optimization problem, high speed convergence and high efficiency are the main advantage of COA [26], [27][28].

The outcome of the manuscripts is as following:

- A novel controller with an optimization strategy i.e., MPC-COA for ACC system is introduced in this manuscript.
- Using MPC-COA, a vehicle maintains its present state velocity when it reaches near another vehicle moving with a steady velocity.
- Integrating COA with MPC enables better performance of the controller and helps in achieving stability with maximum convergence speed.
- With minimum input acceleration, the proposed MPC-COA scheme provides comfort and safe driving.

This paper has following sections: Section 2 includes the ACC system design. It includes the vehicle modelling, MPC-COA design strategy and error optimization using the designed algorithm. Section 3 includes implementation of MPC-COA in ACC system on MATLAB platform followed by simulation results discussion and comparison with other controller results for different horizon periods and convergence speed. Lastly, Section 4 discusses the conclusion and future scope of the carried-out work.

2. ADAPTIVE CRUISE CONTROL DESIGN

2.1 *Vehicle Modeling*

The Target Vehicle (TV) and Host Vehicle (HV) are as shown in Fig. 2. For maintaining a desired distance between the two vehicles, the following factors are considered for ACC design.

- Acceleration (a_H) of the host vehicle must decrease until it reaches zero.
- ($d_{error}=d_V-d_d$) must decrease to zero.
- ($\upsilon_{error}=\upsilon_V-\upsilon_H$) must also decrease to zero.

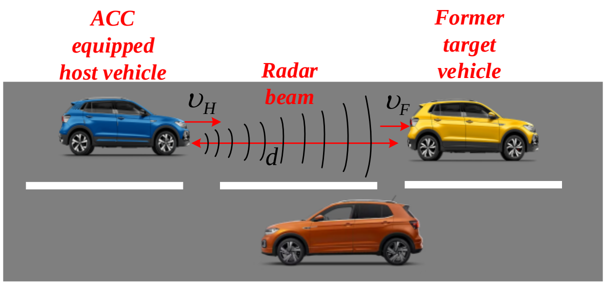

Fig. 2. Working of ACC.

For designing MPC and for analyzing the controller performance, the dynamic model of HV is considered as is denoted in equation 1.

$$M\upsilon_H=Ma_F-r_T \tag{1}$$

where, M is defined as the vehicle's mass, HV's traction force is converted into acceleration which is represented by a_F and travel resistance is denoted as r_T. Equation 2 represents the actuation dynamics of HV.

$$\upsilon_H=f_{Act}\left(x_F,c\right) \tag{2}$$

$$a_F=h_{Act}\left(\upsilon_H\right) \tag{3}$$

The system's output is $y=a_F$. Here, r_T is negligible.

The plant model is designed using state parameters d_{error} and υ_{error} for ACC system. Based on (t_{CHW}) i.e., the time required by HV to reach at the current location of TV and with assumed ending distance for safety margin as d_0 the desired distance d_d is defined by equation 4.

$$d_d=t_{CHW}\upsilon_H+d_0 \tag{4}$$

If the TV stops, the HV stops completely and d_0 is taken as 0. Further, the three state variables considered for the plant are as: $x_1=d_{error}$, $x_2=\upsilon_{error}$ and $x_3=a_H$ as in equation 5.

$$x=\begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \tag{5}$$

The state-space model is represented by equations 6 to 10 as given below,

$$a_H=a_F\left(t\right)\upsilon_H+b_F(t)u \tag{6}$$

$$a_F=C_F\upsilon_H \tag{7}$$

where ,

$$A_F\left(t\right)=-\frac{1}{T_{CAE}} \tag{8}$$

$$B_F(t)=-\frac{K_{CAE}\left(t\right)}{T_{CAE}} \tag{9}$$

$$C_F=1 \tag{10}$$

The engine's time constant of acceleration is represented as T_{CAE} and the time dependent steady-state gain is $K_{CAE}\left(t\right)$.

The system dynamics is split as acceleration and deceleration, further modelled as 1st-order delay system. So, the overall system has three states and its linear state-space model is as represented in equation 11-12,

$$x'=A\left(t\right)x+B\left(t\right)u \tag{11}$$

$$y=Cx \tag{12}$$

and

$$A\left(t\right)=\begin{bmatrix} 0 & 1 & -T_{CHW} \\ 0 & 0 & -1 \\ 0 & 1 & A_F\left(t\right) \end{bmatrix},\quad B\left(t\right)=\begin{bmatrix} 0 \\ 0 \\ B_f\left(t\right) \end{bmatrix} \tag{13}$$

The model represented in equation 11-12 is used for MPC design. It is significant for linearizing the non-linear system about the equilibrium. The discrete model is represented by equations 14 and 15.

$$x_{t+1}=\pi\left(t\right)x_t+\gamma\left(t\right)u_t \tag{14}$$

$$y_t=C_dx_t \tag{15}$$

Further, various state boundaries are defined for the vehicle model to design MPC-COA for AV.

2.2 *MPC design*

This section describes the MPC model design for maintaining a proper distance between the two vehicles i.e. HV and TV. A generalized cost function for MPC problem solution is defined as stated in equation 16.

$$\upsilon_N\left(x_0,u\right)=\sum_{k=0}^{N-1}\left\{L\left(x\left(k\right),u\left(k\right)\right)\right\}+\upsilon_F\left(x\left(N\right)\right) \tag{16}$$

Here, for a specified control input command $u(k)$, a_H, d_{error} and υ_{error} must be converged to origin. The accelerations are limited in the range of $a_{H_{MIN}}=-3.0m/s^2$. The upper range of acceleration is $a_{H_{MAX}}$,where $a_{H_{MAX}}=3(1-0.02\times v_H)m/s^2$ and $a_{H_{MAX}}$ is zero when $v_H=50m/s$. To avoid collision with the TV, it is considered that the minimum distance between HV and TV must be greater than $4.9m$.

The various constraints are listed below.

- Minimum v_F and maximum v_F: Only the longitudinal movement of TV is considered. Both vehicles are assumed to head in same direction.
- Minimum v_H and maximum v_H: Only longitudinal movement of HV is considered.
- The minimum bound of υ_F is fixed as $v_F=15m/s$.
- The maximum value of d is the maximum radar range.

Hence, the range of v_H, d_{error} and υ_{error} can be represented in matrix form as represented by equation 17

$$m=\begin{bmatrix}0\\0\\15\end{bmatrix}\le\begin{bmatrix}d_{error}\\\upsilon_{error}\\\upsilon_H\end{bmatrix}\le\begin{bmatrix}2\\2.5\\50\end{bmatrix}=M \tag{17}$$

Where v_H is attained from a_H.

Several constraints are considered for the controller part. The vehicle acceleration must not be more than $5m/s^2$ and the deceleration must be greater than $-3.0m/s^2$. Then the limit on input is determined as in equation 18.

$$\begin{bmatrix}1\\-1\end{bmatrix}u(k)\le\begin{bmatrix}5\\3\end{bmatrix} \tag{18}$$

Equation 16 represents the MPC optimization issue that must be solved for each iteration as in equation 19 and equation 20.

$$l(x(k),u(k))=x(k)^T Qx(k)+u(k)^T Ru(k) \tag{19}$$

$$V_f(x(N))=x(N)^T Px(N) \tag{20}$$

Where, P, Q and R are positive and definite matrices. For Q=1,R=1 , P represents the solution of which are derived Discrete Algebraic Riccati Equation. The values of for Q and R are obtained in an iterative way. In order to reach the fitness function of minimizing the distance and velocity error, Coati algorithm is used with designed MPC [26].

2.3 COA optimization

The metaheuristic biosphere Coati Optimization Algorithm is explained in this section. The COA flow is depicted in Figure 3. Equation 21 is used to randomly initialize coati's location in the search space.

$$c_{i,j}=min_j+rand.(max_j-min_j),\quad i=1,2,...N,\quad j=1,2,...,d \tag{21}$$

where the j^{th} decision variable is $c_{i,j}$, $rand$ is some value between $[0,1]$ chosen randomly, the uppermost value and lowermost value of the j^{th} decision variable is max_j and min_j respectively. N represents the count of coatis.

The equation 22 uses the N*d matrix which is the mathematical expression for population of the coatis.

$$C=\begin{bmatrix}C_1\\\vdots\\C_i\\\vdots\\C_N\end{bmatrix}_{N\times d}=\begin{bmatrix}c_{1,1}&\cdots&c_{1,j}&\cdots&c_{1,d}\\\vdots&\ddots&\vdots&\iddots&\vdots\\c_{i,1}&\cdots&c_{1,j}&\cdots&c_{i,d}\\\vdots&\iddots&\vdots&\ddots&\vdots\\c_{N,1}&\cdots&c_{N,j}&\cdots&c_{i,d}\end{bmatrix}_{N\times d} \tag{22}$$

The objective function addressed as O is represented in equation 23.

$$O=min(d_{error},\upsilon_{error}) \tag{23}$$

The updating process has two stages as explained below.

a. Exploration stage

At this stage, the plan is successfully made to hunt and attack iguanas. Also, at this stage the most favorable individual in the coatis' population is represented by the position of the iguana. Furthermore, some coatis engage in tree climbing while other coatis patiently await the iguana's descent to the earth. The coati's position climbing the tree is represented by equation 24.

$$C_{i,j}^{P1}=c_{i,j}+rand\times(iguana_j-I\times c_{i,j}); \tag{24}$$

$$\text{for } i=1,2,...,\left\lfloor N/2\right\rfloor \text{ and } j=1,2,...,d$$

Upon falling to the ground, the iguana is positioned in a random location. The equations 25 and 26 are simulated for coatis' population on the ground moving in the direction of the search space.

$$iguana_j^G=min_j+rand\times(max_j-min_j),\ j=1,2,...,d$$

(25)

$$C_i^{P1}:c_{i,j}^{P1}=\begin{cases}c_{i,j}+rand\times(iguana_j^G-I\times c_{i,j}), & O_{iguana^G}<O_i,\\c_{i,j}+rand\times(c_{i,j}-iguana_j^G), & \text{else},\end{cases} \tag{26}$$

$$\text{for } i=\left\lfloor N/2\right\rfloor+1,\left\lfloor N/2\right\rfloor+2,...,N \text{ and } j=1,2,...,m.$$

The updated position is represented in equation 27 is the updated and is used with improved value of objective function.

$$C_i=\begin{cases}C_i^{P1}, & O_i^{P1}<O_i\\C_i & \text{else}\end{cases} \tag{27}$$

where $iguana$ is the iguana's position in the search domain. $iguana_j$ is its j^{th} dimension. The randomly created iguana's position on the ground is $iguana^G$ and its dimension is $iguana_j^G$. The objective function value is represented as O_{iguana^G}. The updated position for the i^{th} coati is C_i^{P1} and its j^{th} dimension is $c_{i,j}^{P1}$ and its objective function is O_i^{P1}. A random real number between [0,1] is represented as rand. The objective function value is represented as O_{iguana^G}. I is a random integer between the set {1,2}. $\lfloor \cdot \rfloor$ is the better integer function.

b. Exploitation stage

At this stage, the most optimal position in the search space is determined by using the coati's natural behavior of fleeing from predators. A random position is created as represented in equations 28 and 29.The position created is adjacent to each coati's position for the simulation of this behaviour.

$$min_j^{local} = \frac{min_j}{t}, max_j^{local} = \frac{max_j}{t}, \quad t = 1,2,...T. \tag{28}$$

$$C_i^{P2}: c_{i,j}^{P2} = c_{i,j} + (1-2rand) \times \left(min_j^{local} + rand \times \left(max_j^{local} - min_j^{local}\right)\right) \tag{29}$$

for $i=1,2,...,N, \; j=1,2,...d.$

Similarly, equation 30 represents that the newly updated position is suitable only if it makes the objective function value better, where the updated position evaluated for the coati is C_i^{P2} and its dimension is $c_{i,j}^{P2}$. The objective function value is represented as O_i^{P2}. max_j^{local} and min_j^{local} signifies the decision variable's local maximum and minimum value. t represents the iteration number and rand is the random value between [0,1].The updating process from equations 24 to 30 repeats until the final iteration of the algorithm [27].

The minimized error in distance and minimized error in velocity are obtained at the end of every COA iteration.

$$C_i = \begin{cases} C_i^{P2}, & O_i^{P2} < O_i \\ C_i & \text{else} \end{cases} \tag{30}$$

3. SIMULATION OUTCOME AND EXPLANATION

This section describes the ACC control technique based on novel MPC-COA equipped in HV with actuation model parameters as stated in Table 2.

Table 2. Actuation model details

Parameter	Value	Unit
T_{CHW}	1.600	s
t_s	0.050	s
T_{CAE}	0.460	s
K_{CAE}	0.732	-

The simulation work is carried on MATLAB platform. Also, the performance of the introduced approach is evaluated and compared with previous conventional approaches such as LQR and MPC [26].

3.1 Simulation result of MPC-COA

This simulation results of the novel MPC-COA strategy is elaborated in this section in Fig.4. The initial HV acceleration is assumed as $15 \, m/s^2$. The actuation parameters for the model is listed in Table 2.

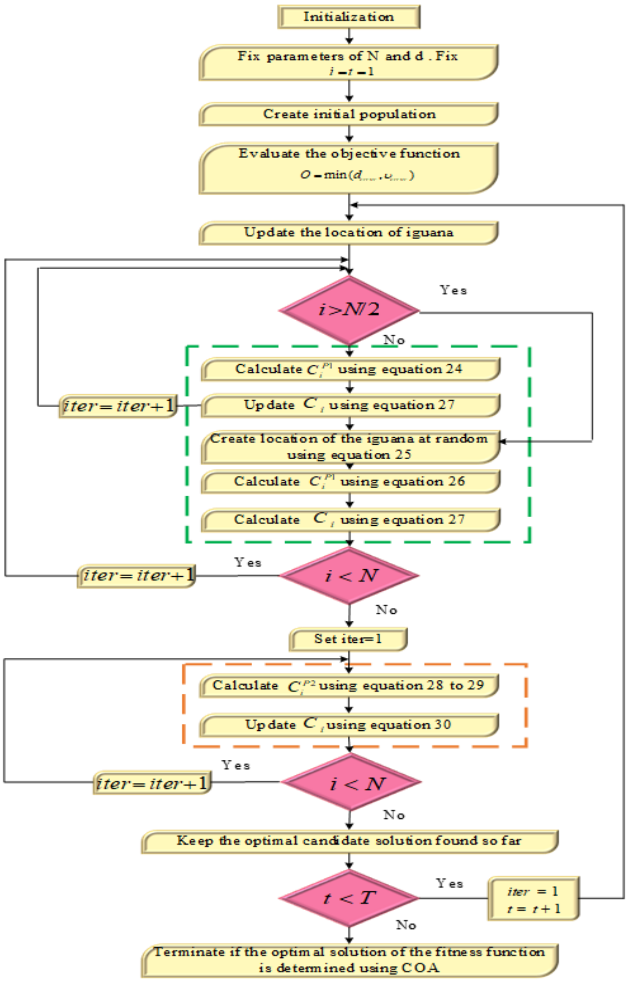

Fig. 3. Flowchart of COA optimization

For quadratic cost function having linear constraints,quadratic programming i.e., qp-solver in MATLAB is used to obtain the desired results that include desired input acceleration, velocity error, distance error and the host vehicle acceleration for prediction horizon(N) of 20 .

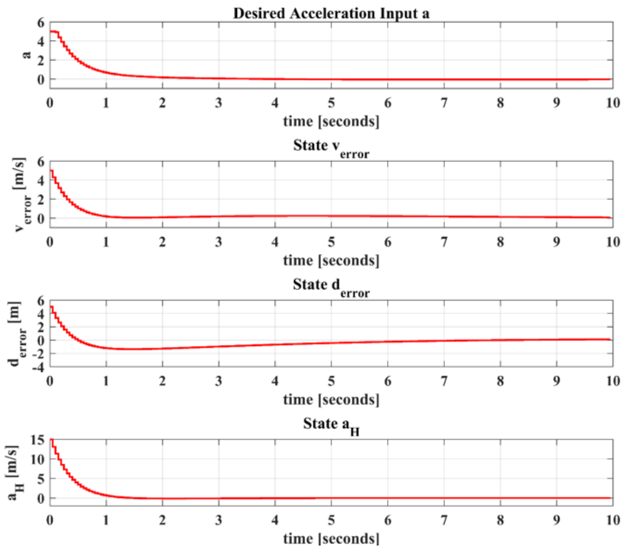

Fig.4. Outcomes of MPC-COA

From the above Fig. 4, it is observed that, d_{error} and υ_{error} is successfully minimized by introduced MPC-COA controller. The negative d_{error} suggests that the difference between the two distances, maintained and actual distance is zero. It does not suggest that the vehicle crashes into other. Also, a constant velocity of 15m/s is maintained. Within a minimum time duration, a_H and υ_{error} also converge to zero. The negative υ_{error} suggests that both the vehicles are moving towards each other with zero υ_{error} and after sometimes, they travel with equal velocity.

3.2 Varying Horizon N

In this section, the MPC-COA outcome with respect to variable N is obtained on MATLAB and is plotted in Fig.5.

In case of existing approaches [26], the controller does not stabilize and performs weakly for N=5 and N=10 but the newly introduced scheme significantly reduces error even at N=10. Only for N=20 and above the controller is stable. As shown in Fig. 5.

The error values for varying N for different cases of MPC-COA is tabulated in Table 3.

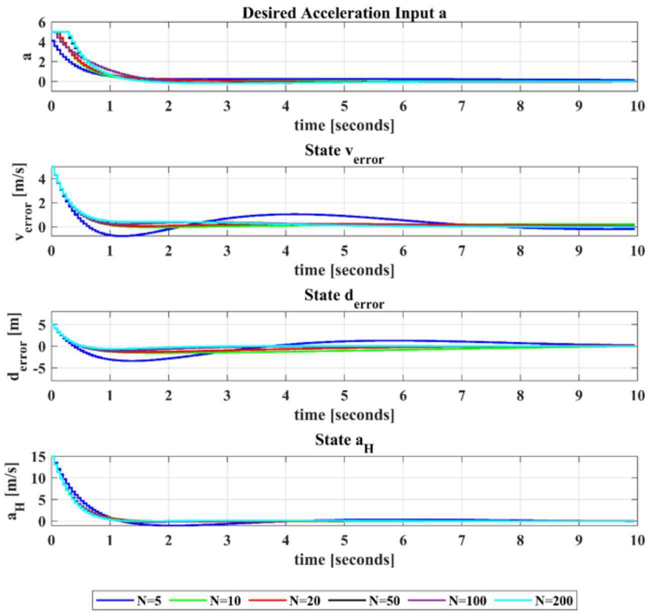

Fig.5. MPC-COA output with varying N

Table 3. Error with varying N

Horizon N	*Best*	*Std*	*Mean*	*Worst*
5	15.1198	25.3381	28.2197	150.6112
10	1.3615	9.4839	4.0937	62.9449
20	0.3032	6.5484	2.5484	38.5339
50	0.1758	4.1885	1.6802	26.1912
100	0.1727	4.7731	1.7007	31.7959
200	0.1089	4.3666	2.0641	28.9226

The Table 3 clearly shows that the error values converge from N=5 to N=200.For N=200, best convergence is observed but the computational time is maximum. Thus, N=20 is the most convenient prediction horizon.

3.3 Variable state weight Q

The effect of varying Q on MPC-COA output is plotted in Fig.7. The result shows that for Q=0.1*I, the designed controller response is abrupt. Thus such case is neglected for a smooth ride. For Q=1, the output of controller is smooth with proper error converge to zero. This condition also satisfies all the constraints. Q is an identity matrix multiplied by different weights as 0.1, 1 and 10.

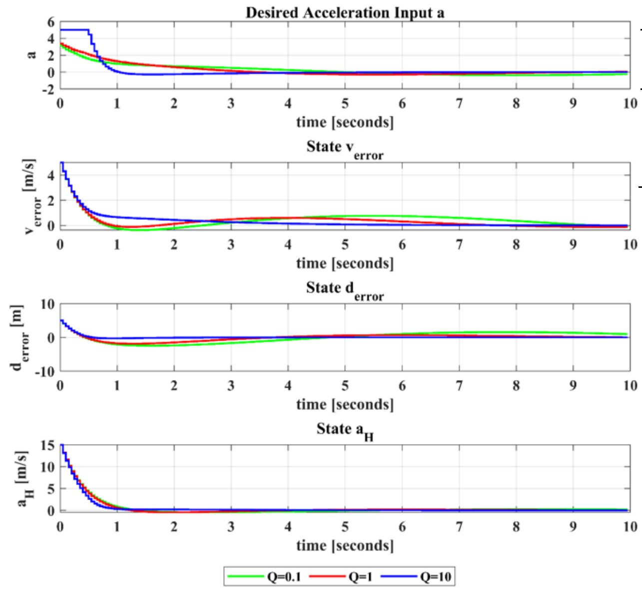

Fig.6. MPC-COA output with varying Q

The error values for varying Q for different cases of MPC-COA is tabulated in Table 4.

Table 4. The observed error values for different Q.

Q	Best	Standard	Mean	Worst
0.1	2.835	11.428	9.766	54.410
1	0.261	5.362	2.854	27.334
10	0.506	6.343	3.122	35.012

3.4 *Variable state weight R*

Similarly, in this section, the effect of varying R on MPC-COA output is plotted in Fig.8. For R=1, the output of controller is smooth with proper error converge to zero.

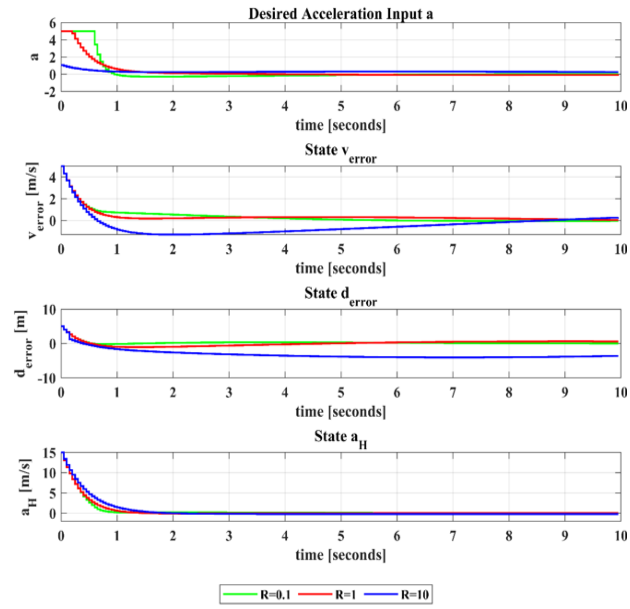

Fig.7. MPC-COA output with varying R

Similarly, the error values for varying Q for different cases of MPC-COA is tabulated in Table 4.

Table 5. The observed error values for different R.

R	Most accurate	Standard	Mean	Least accurate
0.1	0.281	5.257	1.628	26.872
1	0.214	5.142	1.631	25.602
10	1.383	11.543	7.346	60.853

Therefore, it is observed that with Q=1 and R=1, MPC-COA controller performs most effectively and efficiently.

3.5 *Performance comparison*

Several traditional techniques like MPC and LQR are used to compare and analyse the overall performance of introduced MPC-COA control strategy as shown in Fig.9. The v_{error} and d_{error} is converge faster with MPC-COA and its performance is better as compared to the conventional MPC and LQR controllers. Also, the existing controllers cause uncomfortable situation for passengers and drivers because of greater settling time value as compared to MPC-COA. Thus, with minimum settling time, the introduced scheme ensures comfort and safe driving and attains stability at faster pace compared to MPC and LQR.

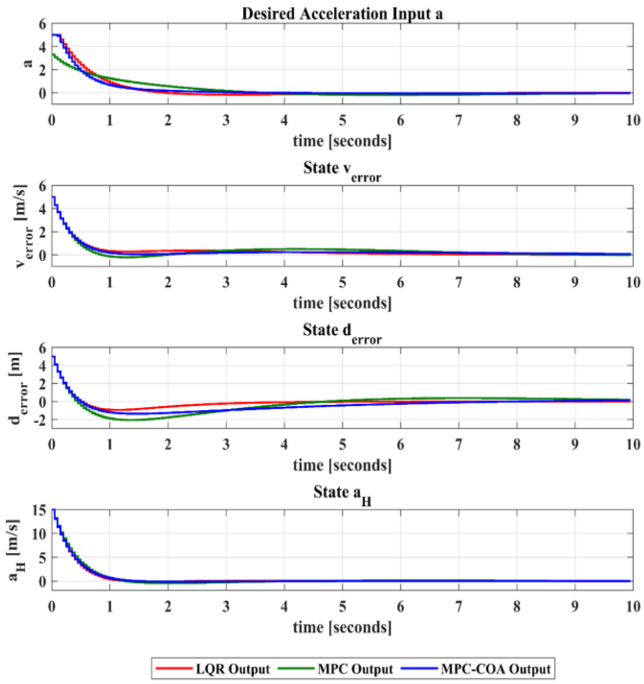

Fig. 8. Comparison of outputs.

Also, the distance error and error in velocity are improved at a much faster rate with the help of MPC-COA controller as compared to the conventional MPC and LQR controllers.

Further the MPC -COA based ACC is equipped in the following vehicle with different vehicle parameters listed in Table 6.

Table 6. Parameters of leading vehicle and following vehicle for MPC-COA based ACC.

Parameters	Leading Vehicle	Following Vehicle
Reference speed(m/s)	20	20
Initial speed(m/s)	15	30
Initial position(m)	30	0
Initial relative distance(m)	30	30
Final relative distance(m)	38	38

Based on Fig. 10 and Fig.11, it is observed that MPC -COA equipped following vehicle performs very efficiently. The various observations are as:

- The leading target vehicle has speed of 15 m/s during starting
- The following host vehicle has speed of 30 m/s during starting
- Both the vehicles must attain a reference speed of 20 m/s
- In order to avoid collision, the following vehicle first de-accelerates and later accelerates to attain an speed of 20m/s ,at the same time maintaining a safer distance with the leading vehicle

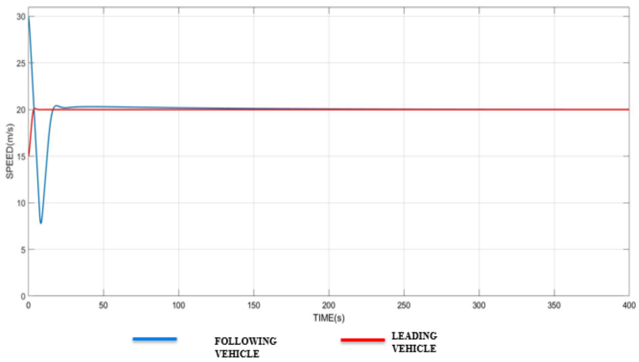

Fig. 9. Speed of following vehicle and leading vehicle.

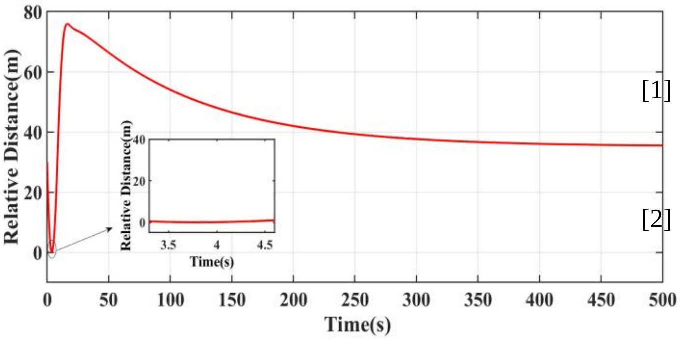

Fig .10. Relative distance between the two vehicles.

- In order to avoid collision, the following vehicle first de-accelerates and later accelerates to attain an speed of 20m/s, at the same time maintaining a safer distance of 38m with the leading vehicle.

4. CONCLUSION

In this manuscript, the MPC-COA was successfully designed and implemented to provide the necessary stability for maintaining safe distance between the vehicles. Using the MATLAB software, the proposed technique is simulated, and the results are compared with conventional controllers like LQR and MPC.

The analysis is carried out with performance metrics like desired acceleration input, velocity error, distance error and acceleration of the following vehicle i.e. host vehicle. The MPC-COA increases the vehicle-following abilities of ACC equipped vehicles and offers drivers, the vehicle-following time gaps that are less time-consuming than those offered by existing ACC systems. Attaining the fitness function of MPC using COA in the proposed scheme makes the control system more efficient with high convergence speed. The MPC-COA based ACC is evaluated for a number of prediction horizons and it performs most efficiently for a prediction horizon of N = 20. Additionally, the controller's implementation with different state weights Q and R were used to demonstrate that the vehicle with ACC can adjust and keep the same velocity while the target vehicle in front of it accelerates, which is what ACC is ultimately intended to do. Overall, the results of MATLAB simulation show the simplicity of the proposed novel MPC-COA strategy and proves its ability for maintaining a vehicle in designated constraints. The MPC controller could be further relate to other control regimes to create a hybrid controller that combines their merits that would be intriguing in future.

ACKNOWLEDGEMENT

The author wishes to extend sincere appreciation and gratitude to her guide and co-guide for their unwavering support during the whole of this project.

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