Weight Changing Model Predictive Controller for Adaptive Cruise Control with Multiple Objectives

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***Abstract*—In this work, model predictive control (MPC) problem with multiple objectives was solved to formulate adaptive cruise control of the passenger vehicle, hierarchical control architecture was implemented in which desired acceleration calculated by upper controller was translated to throttle and brake output by the lower controller. To propose the optimum acceleration a vehicle following model was established and constant time headway policy was used to propose safe distance. An optimization problem was formulated whose performance index mathematically included performance, safety, comfort, and economy. Quadratic programming was used to solve and implement receding horizon control. Investigating the impact of choosing different weighing parameters, a changing weights strategy was formulated which can adapt to the driving conditions by changing the weighing parameters within limits to get better results. Simulations were performed for both the constant and changing weights, Results demonstrated considerable improvement in weight changing with conditions.**

Keywords-model predictive control; adaptive cruise control; weight tuning; fuel economy; ride comfort; multiple objectives

I. INTRODUCTION

Owing to the massive increase in a number of vehicles using these driver assistance systems Industry is now focusing on adaptability, safety, ease, and implications for traffic flow and environment. [1]

Adaptive cruise control is basically more advanced and nurtured form of traditional cruise control. Cruise control in its early form let the driver maintain a specific speed during cruising on the highway [2]. With the technological advancements, it became more and more smart and revolutionized to adaptive or smart cruise control. Commercialised adaptive cruise control can maintain a safe distance between the vehicles or follow the velocity of the preceding vehicle [3]. Safety had been a concern from the start of development of such systems so with breakthroughs in technologies this is an issue is addressed to a workable extent. Similarly, comfort is also one of the main parameter in the success of any autonomous system so it also was in consideration of designers [4].

Lesswe work has been done to compile all the objectives, to consider performance comfort, fuel economy and ensuring safety as well [2]. A number of different control techniques were used to formulate multiple objective problem but model predictive controller is the most suitable option as it can account constraints [5][6]. Most of the work done focused the one lane vehicle following. Which considers that the preceding vehicle speeds up or slows down but remain in front of the host vehicle and the ride is not interfered from vehicles from other lanes. Whereas in the real driving scenarios there could be possibilities that another vehicle change their lane while host vehicle keeps the lane. In these cases, the preceding subject vehicle will change causing sudden changes in relative velocity and relative distance, that could affect the performance of the host vehicle. Performance of the controller can be affected with overshoots in such conditions and real-time weight tuning could give better results [7]. More work is needed to be done to improve the sensitivity of tuning strategy also while considering the limits above which controller output deteriorates.

This work is focused on adding more to the previous work, which involves designing of multi-objective model predictive controller ACC controller and a weight changing strategy that can adapt to difficult driving scenarios. A number of difficult driving conditions are then simulated, results were compared with both the constant weights and changing weights where results showed considerable improvement.

II. CONTROLLER DESIGN

Control architecture is chosen to be hierarchical. In which the upper controller computes desired the acceleration that is input to the lower controller. Lower controller deals with vehicle dynamics and actuators and translates this acceleration to brake and throttle command to the vehicle. As this work is focused on the upper controller the lower controller is based on the inverse vehicle dynamics. More details of which could be found in [2], [3].

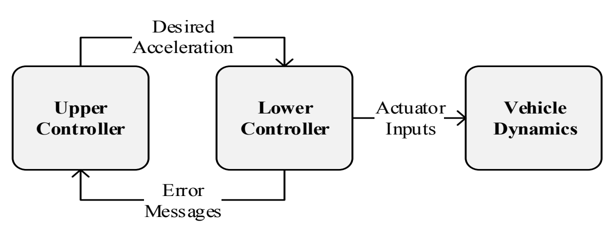

Figure 1. Control architecture.

To predict the future information a predictive model has to be established which has to simple and accurate. While receiving or communicating information of vehicle driveline systems a time delay can be caused by actuators, sensors etc. So, for the timely manipulation of the signal, it is necessary to compensate for that delay, it is done by implementing first-order lag [7].

$$a = \frac{E}{Y \times s + 1} \tag{1}$$

If subscript $_p$ and $_f$ represents the preceding vehicle and following vehicle, k represents the current iteration, $s_f(k)$, $v_f(k)$, $a_f(k)$ is the corresponding distance, speed and acceleration.

$$\begin{aligned} s_f(k+i|k) &= s_f(k) + v_f(k) \times (iT_s) + \frac{1}{2} a_f(k) \\ &\quad \times (iT_s)^2 \\ v_f(k+i|k) &= v_f(k) + a_f(k) \times (iT_s) \\ a_f(k+i|k) &= \frac{E}{Y \times s + 1} a_{fdes}(k) \end{aligned} \tag{2}$$

$s_f(k+i|k)$, $v_f(k+i|k)$, $a_f(k+i|k)$ are the predicted speed, velocity and acceleration at $k+i$ iteration. Where a_{fdes} (k) is the desired acceleration of following vehicle. E and Y are the system gain and delay respectively.

The three-state space model for the car-following system is formulated as:

$$\begin{gathered} \dot{x}_f(k+i|k) = A' * x_f(k) + B' * a_{fdes}(k) \\ x_f(k+i|k) = \begin{pmatrix} s_f(k+i|k) \\ v_f(k+i|k) \\ a_f(k+i|k) \end{pmatrix} \\ A' = \begin{pmatrix} 0 & 1 & T_s \\ 0 & 0 & 1 \\ 0 & 0 & -\frac{1}{Y} \end{pmatrix} B' = \begin{pmatrix} 0 \\ 0 \\ \frac{E}{Y} \end{pmatrix} \end{gathered} \tag{3}$$

Discretization yields to

$$\begin{gathered} x_f(k+i|k) = A \cdot x_f(k) + a_{fdes}(k) \cdot B \\ A = \begin{pmatrix} 1 & T_s & {T_s}^2 \\ 0 & 1 & T_s \\ 0 & 0 & 1 - \frac{T_s}{Y} \end{pmatrix} B = \begin{pmatrix} 0 \\ 0 \\ T_s \frac{E}{Y} \end{pmatrix} \end{gathered} \tag{4}$$

III. Safe Distance Model

Inter-vehicular distance is very important in the design of adaptive cruise control because if the distance is too small the driver may feel insecure, whereas if it is very large interception from other vehicles could increase. A large number of car manufacturers opt to adopt constant time headway policy for evaluating desired distance. Stated as

$$d_{des}(k) = \tau v_f(k) + d_{safe} \tag{5}$$

d_{des} is the desired safe distance, d_{safe} is the safe stopping distance, τ is the time constant

IV. Performance Index

Usual objectives for the multiple objective adaptive cruise control are tracking economy and comfort. Adaptive cruise control system must follow vehicle velocity and distance so tracking performance could be termed as

$$\begin{aligned} J_{track}(k+i|k) = w_d\big(\Delta d(k+i|k)\big)^2 \\ + w_v\big(\Delta v(k+i|k)\big)^2 \end{aligned} \tag{6}$$

The economy of an adaptive cruise system could be directly related to acceleration, so the economic performance index could be termed as

$$J_{economy}(k+i|k) = w_a a_f(k)^2 \tag{7}$$

Comfort for an adaptive cruise control system is related to jerk, so it is related to the rate of change of acceleration in the performance index

$$J_{comfort}(k+i|k) = w_{da} \dot{a}_{fdes}^2(k) \tag{8}$$

Overall performance index becomes

$$\begin{aligned} J(k+i|k) = J_{track}(k+i|k) \\ + J_{economy}(k+i|k) \\ + J_{comfort}(k+i|k) \end{aligned} \tag{9}$$

where

$$\begin{aligned} \Delta d(k+i|k) = s_p(k+i|k) + d_{initial} \\ - s_f(k+i|k) - d_{des}(k+i|k) \\ d_{des}(k+i|k) = \tau v_f(k+i|k) + d_{safe} \\ \Delta v(k+i|k) = v_p(k+i|k) - v_f(k+i|k) \end{aligned} \tag{10}$$

w_d is weight coefficient of distance error, w_d is the weight coefficient of velocity error, w_d is weight coefficient of acceleration, w_{da} is the weight coefficient of the rate of change of acceleration, s_p is the actual driving distance of preceding vehicle, $d_{initial}$ is the initial distance between two vehicles.

The said performance index is transformed to depend on the state variables and quadratic programming is used to solve for the desired acceleration. Table I. shows the parameters used in this study

TABLE I. PARAMETERS

Parameter	Value	Parameter	Value	Parameter	Value
E	1	w_d	2.9	$w_{v\,max}$	13
Y	0.37	w_v	11.5	$w_{a\,min}$	2
τ	1.5	w_a	3.5	$w_{a\,max}$	5
d_{safe}	5 m	w_{da}	0.01	Δd_{min}	-12
$a_{fdes_{min}}$	-4m/s2	$w_{d\,min}$	2	Δd_{max}	12
$a_{fdes_{max}}$	2m/s2	$w_{d\,max}$	4	Δv_{min}	-12
T_s	0.1s	$w_{v\,min}$	10	Δv_{max}	12

V. WEIGHT CHANGING STRATEGY

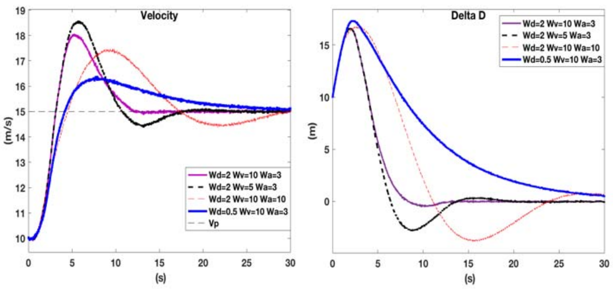

Figure 2. Response with different constant weights.

Corresponding simulations depicts a case when the host vehicle with 10m/s velocity detects a preceding vehicle at the distance of 30m ahead (because of the lane change) traveling at 15m/s. The response of the host vehicle varies with changes in the parameters.

Lesser the value of w_d slower the response of the vehicle to reach desirable distance. Bigger the values of w_v and w_d quicker is the response to overcome velocity and distance error but it also results in overshoot. Whereas increasing the value of w_a helps reducing the overshoot but the overall response is slow.

During driving, there could arise different possibilities which may require fast responses in some cases slow, so only changing one parameter for relatively complex driving conditions could not fulfill control objectives.

Weight parameters are selected from various hit and trail runs but within a specific range they have a considerable change in the output but beyond certain limits, they can completely deteriorate results.

In order to change parameters in accordance with driving conditions, their relation has to be developed with affecting variables which in this case are Δd and Δv. Desired control objectives with changing values of Δd and Δv are summed up in the Table II.

TABLE II. DRIVING CONDITIONS & DESIRED RESPONSE

Driving Condition	$\Delta d > 0$, $\Delta v < 0$	$\Delta d < 0$, $\Delta v > 0$	$\Delta d < 0$, $\Delta v < 0$	$\Delta d > 0$, $\Delta v > 0$
Desired Response	Smoothly Decelerate	Smoothly Accelerate /Decelerate	Quickly Decelerate	Normal Operation
w_d	Small	Large	Large	Constant
w_v	Large	Small	Large	Constant
w_a	Large	Large	Small	Constant

For this to implement using normalization maximum and minimum boundaries should be defined, maximum and minimum values of $w_d w_v w_a$ are linked with Δd & Δv as mentioned in the Table III.

TABLE III. LIMITS FOR NORMALIZATION

Δd_{min}	$w_{d\,max}$	Δv_{min}	$w_{v\,max}$	$(\Delta d + \lvert\Delta v\rvert)_{min}$	$w_{a\,max}$
Δd_{max}	$w_{d\,min}$	Δv_{max}	$w_{v\,min}$	$(\Delta d + \lvert\Delta v\rvert)_{max}$	$w_{a\,min}$

Where Δd_{min} , Δd_{max} Δv_{min} , Δv_{max} are the minimum and maximum ranges of Δd & Δv respectively. Changing the value of w_a is not straight forward it has to related to both Δd & Δv, so the values of w_a are related to the cumulative sum of Δd & Δv as shown in the table. Where $w_{a\,min}$, $w_{a\,max}$, $w_{v\,min}$, $w_{v\,max}$, $w_{d\,min}$, $w_{d\,max}$ defines the maximum and minimum bounds for weighting parameters $w_{d,} w_{dv}$ & w_a respectively.

Controller can give a stable output only within specific range of values for the weighting parameters, so in order to guarantee the stability of the controller value of these parameters must vary within that stable output range. So, lot of simulations were run to decide these maximum and minimum values. Robustness of the controller can also be verified by the simulations if it's performance is stable for different driving conditions. It is to be noted that if values of Δd & Δv exceeds the defined limits their value is taken to be maximum/minimum defined limit in order to maintain sensitivity.

VI. SIMULATIONS AND DISCUSSIONS

Three different kinds of scenarios are simulated in which host vehicle keeps its lane but different responses are required due to change in the subject preceding vehicle

Case-1 Positive cut out from Preceding Vehicle

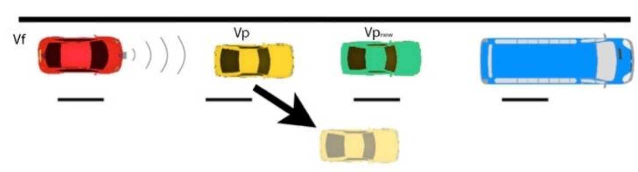

Figure 3. Positive cut out from preceding vehicle.

Consider a case when the host vehicle is driving with a velocity of 25 m/s. Due to positive cut out of the preceding vehicle to another lane, a new preceding vehicle is detected with a velocity of 15 m/s & 48 m in front of the host vehicle. As $\Delta d = 5.5\ m$ & $\Delta v = -10\ m/s$ so smooth deceleration is required in this case. Values of the weighting parameters are adjusted as mentioned in the table. It can be observed that both the constant weights and changing weights can gain stabilization while retaining the safe distance but new strategy also manages to prevent the overshoot.

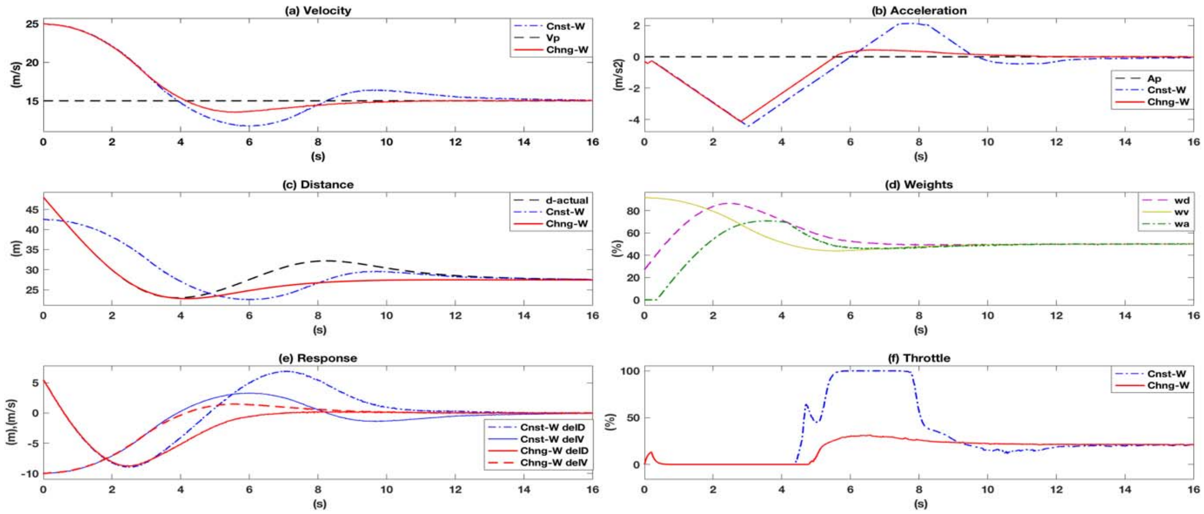

Figure 4. Response of host vehicle for Case-1.

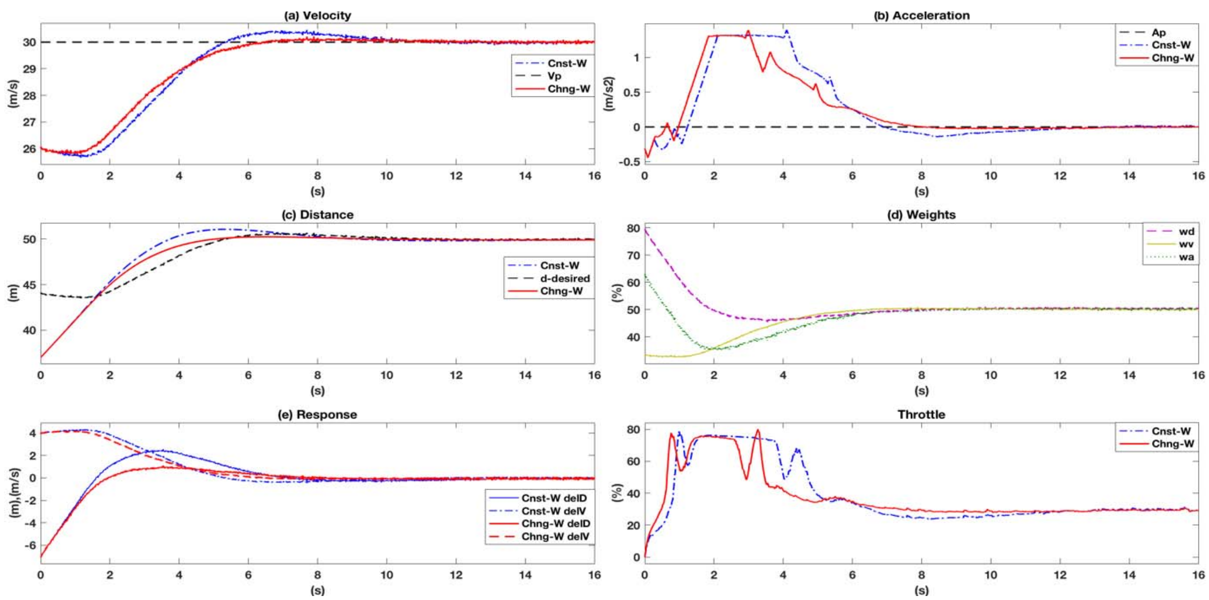

Figure 5. Response of host vehicle for Case-2.

Case-2 Positive cut into the lane

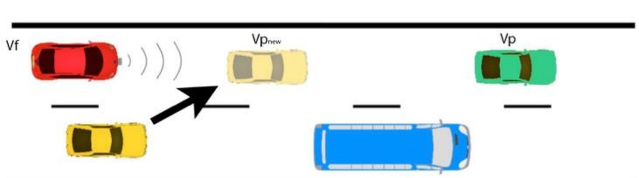

Figure 6. Positive cut into the lane.

Consider a case when the host vehicle is driving with a velocity of 26 m/s. Due to positive cut in from the other lane new preceding vehicle is detected with a velocity of 30 m/s & 36 m in front of the host vehicle. As $\Delta d = -6.5\, m$ & $\Delta v = 4\, m/s$ so w_d should be large and w_v should be relatively lower as mentioned in the table. It can be observed that both the constant weights and changing weights handles this situation very well but response from the new strategy is relatively smoother

Case-3 Negative cut into the lane

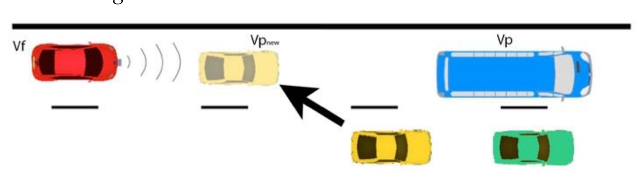

Figure 7. Negative cut into the lane

Consider a case when the host vehicle is driving with a velocity of 23 m/s. Due to negative cut in from the other lane the new preceding vehicle is detected with a velocity of 15 m/s & 36 m in front of the host vehicle. So $\Delta d = -3.5m$ & $\Delta v = -8m/s$. As both the Δd & Δv are negative, w_d and w_v should be large to avoid collision meanwhile w_a should be relatively lower as mentioned in the table. While both the constant weights and changing weights handles this situation, new weight changing strategy also prevents overshoots.

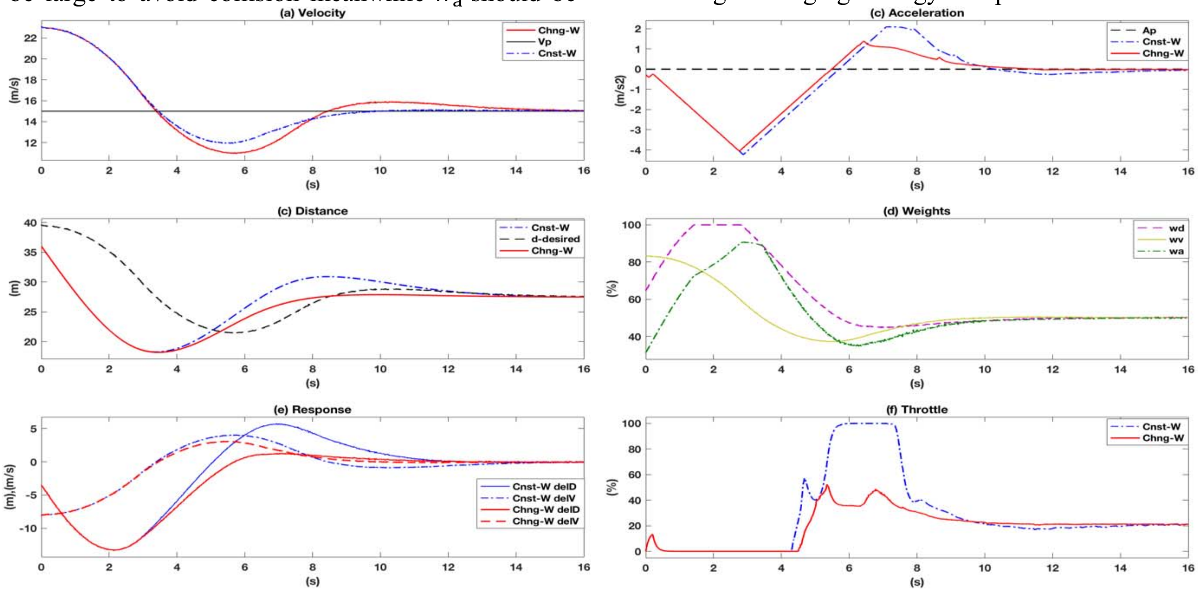

Figure 8. Response of host vehicle for Case-3.

VII. Evaluating Performance and Economy

Performance can be referred to as tracking ability. To measure the goodness of tracking, terminating values of the following function are used

$$TEI = \frac{1}{T}\int_0^T \left(\left|\Delta d(t)\right| + 0.1\left|\Delta v(t)\right|\right) dt$$

where T is the simulation time for ACC, Δd is in meter, and Δv is in m/sec.

TABLE IV. Tracking Performance

Case	Constant Weights	Changing Weights	Improvement
1	1.7309	1.0972	36%
2	0.5716	0.4066	28%
3	2.1452	1.7285	19%

Fuel economy of the following car is measured by FCM

$$\text{FCM} = \frac{1}{S}\int_0^T Q_{eng} dt$$

TABLE V. Fuel Economy

Case	Constant Weights	Changing Weights	Improvement
1	9.4539	7.3359	22%
2	10.446	10.07	4%
3	9.6723	8.7488	9%

where T is the simulation time for ACC, S is traveling distance of the following car in kilo meter, Q_{eng} is the fuel rate of the engine in liter/sec.

VIII. Conclusion

In this paper a weight changing strategy for real-time tuning of weight parameters is proposed, Relation between changing driving conditions and parameter values were established and normalization was used to change parameters within a specific range which always guarantee a stable output. Different possible cases were simulated in MatLab/Simulink and comparisons were discussed. Results showed that the proposed strategy can improve fuel economy while keeping performance in check.

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