Model Predictive Adaptive Cruise Control

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***Abstract*—In this paper, the Model Predictive Control (MPC) structure is used to solve the ACC problem and the performance of the design is tested using a realistic nonlinear vehicle model. A hierarchical control structure is used where MPC is placed on top of the hierarchy while the actuators are controlled by simpler linear controllers. The real-time optimization needed for MPC is solved using Quadratic Programming (QP). The performance of the MPC is tested under different traffic scenarios. The control system is able to determine the ongoing scenarios autonomously, using available measurements.**

***Keywords*—Adaptive Cruise Control, Model Predictive Control, receding horizon, powertrain modeling**

I. Introduction

Adaptive Cruise Control (ACC) System, as an extension to conventional cruise control, aims to maintain relative speed and relative distance with a preceding vehicle autonomously and acts as a conventional cruise control system in the absence of a preceding vehicle. The ACC system, replaces the driver's longitudinal control responsibility, through its longitudinal acceleration and deceleration maneuvers without any lateral control intervention using its on-board radar system which measures relative speed and relative distance between vehicles. The inter-vehicle distance is maintained with either a constant time headway policy or using a specified vehicle distance both of which are defined by the driver. The control of the system must provide this desired distance without causing a collision. Furthermore, the maximum acceleration and minimum deceleration is kept within pre-specified limits in order to guarantee comfort and safety.

The comfort issues related to the use of ACC have been treated due to the unconventional longitudinal acceleration and deceleration result due to the brake and throttle manipulations of the system [1]-[2] Beyond acceleration performance, jerk behavior of the ACC equipped vehicle is also being investigated widely [2]-[4].

Numerous control algorithms have been used in order to maintain the inter-vehicle distance and relative velocities between vehicles. In [5], an ACC system is modeled as a hybrid system with constant acceleration, smooth acceleration, and linear state feedback controllers. In [6], Adaptive Neural Network scheme has been used, in a platoon in order to solve the traffic stability problem.

There are different policies to regulate the inter-vehicle distance between the ACC equipped vehicle and the target vehicle. In [7], a constant distance policy is selected to control the speed and distance of a platoon using sliding mode control approach. Constant time headway is also a method widely used to calculate the desired following distance as a function of the ACC vehicle speed and a constant time parameter selected by the driver [8].

Model Predictive Control (MPC) is a well-known control technique based on online optimization procedure with a receding horizon approach [9],[10]. In a MPC problem, using the system model, future behavior of the system is predicted and optimal control inputs that minimize the specified cost function are generated. If required, objective, state or output constraints can also be integrated into the optimization process. Since the numerical solutions of the MPC problem in real-time result in a substantial computational load, the popularity of the control systems remained limited until the hardware technology reached a certain level of computational speed [11].

MPC algorithm has been used in several works to achieve the ACC and cruise control problem, with various schemes. In [12], using MPC structure, a cruise control system is designed for a heavy duty vehicle, with the help of the GPS and digital mapping to minimize fuel consumption. In [3], MPC framework has been used to solve the ACC and Stop and Go problem, under various traffic scenarios. The study does not take into account the nonlinear vehicle models and the control system is studied for linear inter-vehicle dynamical model. In [11], typical variation of MPC control has been investigated to solve the ACC problem and the computational performances are compared for a simple benchmark traffic scenario. In [13], the ACC problem is solved using MPC algorithm where the design parameters includes also the fuel consumption and comfort criteria. In [2], the performance of the MPC topology is studied during transitional maneuvers of ACC and the collision avoidance performance and the acceleration limits of the system are examined.

Most of the theoretical ACC studies with MPC framework do not consider the performance of the controller under realistic vehicle models, which can more specifically be used for performance evaluation. In this paper, MPC algorithm is formulized in order to solve ACC problem and the designed control algorithm is tested using a high fidelity nonlinear vehicle model. The vehicle model includes, single track vehicle dynamics model, tire model, driveline and engine subsystem models. In order to set a realistic scenario, the behavior of the preceding vehicle is also described with a similar vehicle model. The performance is evaluated under different scenarios

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and ACC equipped vehicle can determine on-going scenario based on the information gathered by its on-board sensors.

The described control system has a hierarchical architecture comprising of two levels. The high level defines a desired acceleration level for the given scenario using the real time optimization methodology. The low level control applies throttle and brake maneuvers to maintain this desired acceleration level. MPC framework facilitates to formulize the comfort and performance index with a closed-loop fashion using a cost function which is to be minimized in real-time. Moreover, the receding horizon structure provides to obtain an optimal control action based on the prediction of the future behavior of the dynamical systems. Hence, this typical formulation enables to implement all desired performance index quantitatively with respect to other linear control structure like in [14].

Model Predictive Control has been formalized as follows. First, a descriptive dynamic model for an ACC equipped vehicle is obtained. A quadratic performance index has been selected such that the required performance criteria of maintaining the relative speed and relative distance are satisfied. The acceleration limits and performance measures are subjected to the performance index as constraints. Then, the real time optimization problem is solved at each sampling time for a defined horizon. The control action belonging to the current time is applied to the system. The horizon is shifted one time sequence to the future and the optimization procedure is repeated.

The rest of this paper is organized as follows: In Section II, the nonlinear vehicle model is defined by introducing key dynamic equations and subsystems of the model. In Section III, the control structure is presented under linear model of MPC structure, prediction model performance criteria and constraints and MPC formulation sub-sections. In Section IV, some important results of the simulations are presented. The paper is concluded in Section V.

II. MODELING

The model described for representing the vehicle longitudinal dynamics consists of several subsystems. As vehicle dynamics representation, a single track vehicle model is selected. Although lateral dynamics has a secondary importance in the ACC problem, some traffic scenarios require steering maneuvers. Front and rear wheel dynamics are used to calculate the longitudinal and lateral forces considering longitudinal slip and side slip angles. Driveline dynamics and an automatic transmission subsystem are also introduced using automatic transmission gear shifting logic. Aerodynamic resistance force and rolling resistance are introduced in the system equation for the longitudinal force balance.

A. Vehicle Dynamics

To represent the vehicles longitudinal and lateral dynamics, a nonlinear single track model augmented with a longitudinal dynamics model is used [14]. The augmented model used here includes both lateral and longitudinal tire forces and is shown in Figure 1.

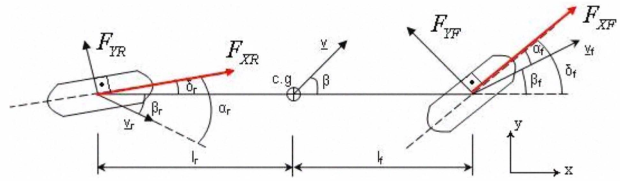

Fig. 1. Augmented single track model

$i=r,f$ is used to denote the front (f) or rear (r) tire set. The augmented nonlinear single track model is characterized by the steering angle projection,

$$\begin{bmatrix} \sum F_X \\ \sum F_Y \\ \sum Mz \end{bmatrix} = \begin{bmatrix} -\sin\delta_f & -\sin\delta_r \\ \cos\delta_f & \cos\delta_r \\ l_f\cos\delta_f & -l_r\cos\delta_r \end{bmatrix} \begin{bmatrix} F_{YF} \\ F_{YR} \end{bmatrix} + \begin{bmatrix} \cos\delta_f & \cos\delta_r \\ \sin\delta_f & \sin\delta_r \\ -l_f\sin\delta_f & -l_r\sin\delta_r \end{bmatrix} \begin{bmatrix} F_{XF} \\ F_{XR} \end{bmatrix} \tag{1}$$

the Newton-Euler dynamics equations of motion,

$$\begin{bmatrix} mv(\dot\beta + r) \\ m\dot v \\ J\dot r \end{bmatrix} = \begin{bmatrix} -\sin\beta & \cos\beta & 0 \\ \cos\beta & \sin\beta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_X \\ F_Y \\ M_Z \end{bmatrix} \tag{2}$$

and the equations of kinematics/geometry,

$$\tan\beta_f = \tan\beta + \frac{l_f r}{v\cos\beta} \tag{3}$$

$$\tan\beta_r = \tan\beta - \frac{l_r r}{v\cos\beta} \tag{4}$$

Tire center velocities can be presented in vector form as

$$\vec v_r = v\cos\beta\vec i + (v\sin\beta - rl_r)\vec j \tag{5}$$

$$\vec v_f = v\cos\beta\vec i + (v\sin\beta + rl_f)\vec j \tag{6}$$

The projected tire velocities along the tire longitudinal directions denoted by V_{rxt} and V_{fxt} are calculated using (5) and (6) as

$$V_{rxt} = |\vec v_r|\cos\alpha_r \tag{7}$$

$$V_{fxt} = |\vec v_f|\cos\alpha_f \tag{8}$$

B. *Tire Force Calculation*

Calculation of tire forces is carried out using the Dugoff tire model. The equations describing the Dugoff tire model are given below in equations (9) – (12) as

$$F_{Xi} = f_i C_{Xi} \sigma_i ,\; F_{Yi} = f_i C_{Yi} \alpha_i \tag{9}$$

$$f_i = \begin{cases} 1, & F_{Ri} \le \dfrac{\mu_i F_{Zi}}{2} \\ \left(2 - \dfrac{\mu_i F_{Zi}}{2F_{Ri}}\right)\dfrac{\mu_i F_{Zi}}{2F_{Ri}}, & F_{Ri} > \dfrac{\mu_i F_{Zi}}{2} \end{cases} \tag{10}$$

$$F_{Ri} = \sqrt{(C_{Xi}\sigma_i)^2 + (C_{Yi}\alpha_i)^2} \tag{11}$$

where σ_i and α_i are longitudinal tire slip and sideslip angle respectively. Longitudinal slips are calculated by the following equation set:

$$\sigma_f = \begin{cases} \dfrac{R.\omega_f - V_{fxt}}{R.\omega_f} & R.\omega_f > V_{tf} \quad (traction) \\ \dfrac{R_{eff}.\omega_{tf} - V_{fxt}}{V_{fxt}} & R.\omega_f < V_{tf} \quad (braking) \end{cases} \tag{12}$$

C. *Powertrain Dynamics*

A conventional powertrain arrangement can be seen in Figure 2. In the powertrain model, all inertias related to rotating parts are described using equivalent inertia, J_{eq} and it is calculated by;

$$J_{eş} = J_M i_D{}^2 i_T{}^2 + J_D i_D{}^2 + J_T \tag{13}$$

where, J_M, J_D and J_T are the moment of inertias of engine, differential and transmission respectively. i_T and i_D represents the gear and differential transmission ratios respectively.

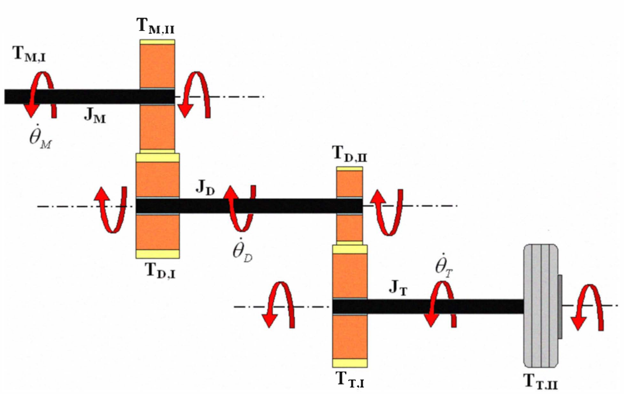

Figure 2. Powertrain model

The net torque at the engine is found by,

$$T_{net,motor} == T_M \cdot i_D \cdot i_T \cdot \eta_T \cdot \eta_D \tag{14}$$

where η_T and η_D are the transmission and differential efficiencies. An automatic gear ratio representation is also added to the model by using a shifting logic at maximum power points of the engine where some hysteresis is being considered in order to prevent consecutive up-and down gear changes.

D. *Engine Representation*

The engine is represented as a look-up table seen in Figure 3. The inputs to the table are throttle and engine speed and the output is the engine torque. The negative torque zones of the engine are also considered and are used in the lower deceleration requirements, with the brake system.

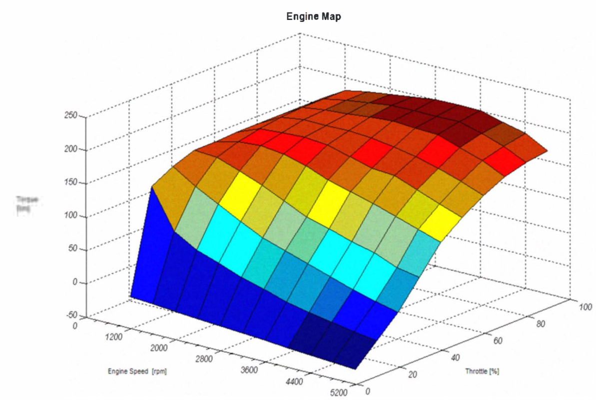

Figure 3. Engine map

The brake intervention is represented by a first order dynamical system. Rolling resistance, aerodynamical drag and road inclination are considered as the resistive forces in the model. Final longitudinal force equivalence is represented by;

$$\sum F_x + F_{drag} + F_{rollingresis\tan ce} + F_{inc} = m\ddot{x} \tag{15}$$

where F_x is the total longitudinal projection of all tire forces, m is the vehicle mass, $\ddot{x}$ is the longitudinal acceleration of the vehicle. F_{drag} is the aerodynamic resistance proportional to $\dot{x}^2$. $F_{rollingresistance}$ is the rolling resistance proportional to $\dot{x}$. F_{inc} is the slope resistance $mg\sin\theta$ for an uphill with slope θ.

III. Control Structure

For the control structure of the equipped vehicle, there are two levels of control systems. At the high level, the MPC algorithm calculates the desired acceleration and deceleration values for the ongoing traffic scenario. For the desired acceleration/deceleration values the low level controller first decides if the throttle or brake action will be applied. After that the desired acceleration/deceleration comment is transferred to an appropriate brake and throttle maneuver and a PI type controller assures that the exact acceleration/deceleration value is obtained in the vehicle. Due to the computational load of MPC the sampling time of the higher level control system is higher. Besides, until the next acceleration/deceleration comment at the end of the next step of the MPC calculation, the previous maneuver must be achieved by the ACC vehicle. A traffic scenario generator is also used in the simulations to change the maneuver of the preceding vehicle and ACC equipped vehicle. The ACC equipped vehicle decides autonomously which scenario is being realized according to the measurements and switches the operation mode between ACC mode or cruise control mode.

A. Linear Model for MPC structure

The inter-vehicle dynamics is represented in the MPC structure by the following linear model [2]:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ew(k) \\ y(k+1) &= Cx(k) + F \end{aligned} \tag{15}$$

where

$$A = \begin{bmatrix} 1 & 0 & T & -0.5T^2 & 0 \\ 0 & 1 & 0 & T & 0 \\ 0 & 0 & 1 & -T & 0 \\ 0 & 0 & 0 & 1-T/\tau & 0 \\ 0 & 0 & 0 & -1/\tau & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & 0 & 0 & T/\tau & 1/\tau \end{bmatrix}^T,$$

$$C = \begin{bmatrix} 1 & -t_h & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$E = \begin{bmatrix} 0.5T^2 \\ 0 \\ T \\ 0 \\ 0 \end{bmatrix} \quad \text{and} \quad F = \begin{bmatrix} -d_0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$x(k) = \begin{bmatrix} d & v_{ACC} & v_{rel} & a & \{a(k)-a(k-1)\}/T \end{bmatrix},$$
$$w(k) = a_p,$$
$$y(k) = \begin{bmatrix} \Delta x & v_{rel} & a & \{a(k)-a(k-1)\}/T \end{bmatrix}$$

T refers the sampling period of the control system, t_h is the time head-way between vehicles, d_0 is the safe distance between vehicles if the vehicles are stopped and τ is the time constant of the low level controller [2]. The states of the model are, inter-vehicle distance *d*, speed of the ACC equipped vehicle v_{ACC}, relative speed v_{rel},, acceleration of the ACC equipped vehicle *a*, and finally jerk of the ACC equipped vehicle, computed as *(a(k)-a(k-1))/T.* Acceleration of the preceding vehicle a_p is introduced into state equation as a disturbance because of the difficulty of the measurement of the state. The output consists of relative distance error Δx, relative speed, acceleration of the ACC vehicle and the jerk of the ACC vehicle [2],[3].

B. Prediction Model

A prediction model is also used to predict the behavior of the model during the prediction horizon, Np. The prediction is realized based on the information of the current states which are used to extrapolate the future behavior of the model until the end of the horizon. Basically, the predicted state variables are calculated along the prediction horizon using future control inputs as:

$$\begin{aligned} &\hat{x}_p(k+N_p|k) = \tilde{A}x(k) + \tilde{B}U(k+N_c) + \tilde{E}W(k+N_p) \\ &+ K_x(x(k) - \hat{x}_p(k|k-1)) \\ &\hat{y}_p(k+N_p|k) = \tilde{C}x(k) + \tilde{D}U(k+N_c) + \tilde{G}W(k+N_p) \\ &- \tilde{F} + K_y(y(k) - \hat{y}_p(k|k-1)) \end{aligned} \tag{16}$$

$\hat{x}_p(k+N_p|k)$ and $\hat{y}_p(k+N_p|k)$ are the predicted state and output vectors calculated at the time step *k* until the end of the prediction horizon N_p. *U(k+* N_c*)* is the control input vector calculated at the end of the optimization until the end of the control horizon, N_c. *W(k+* N_p*)* is the disturbance vector including the estimated future disturbance values along the prediction horizon based on the actual measured states, relative velocity and the acceleration of the ACC vehicle through a first order filter. The values of the disturbance vector are kept constant within the predictive horizon once it is calculated for its first valuei *w(k)*. $\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D}, \tilde{E}, \tilde{F}$ and $\tilde{G}$ are expanded state matrices of the prediction model, obtained by the substitution of each state matrix along the prediction horizon. The prediction model is based on the current measured state together with the future control actions. K_x and K_y are the correction factor that correct the prediction using the state and output errors of the prediction model in the previous time step.

C. Performance Criteria and Constraints

Control objectives are introduced into the optimization process by implementing the output errors into the cost function. Another parameter of the cost function is to penalize the control input's magnitude to get a smooth control action. The defined cost function is minimized in each time step and it can be written as follows:

$$J=\sum_{i=1}^{Np}(\hat{y}_p(k+i|k)-y_{ref}(k+i))^T Q(\hat{y}_p(k+i|k)-y_{ref}(k+i)) + \sum_{i=1}^{Nc-1}u(k+i)^T Ru(k+i)^T \tag{17}$$

where Q and R are the weighting matrices that tune the relative importance of the output vector's elements as well as the magnitude of the control effort. y_{ref} is the reference trajectory of the ACC vehicle based on the maneuver of the preceding vehicle.

A secondary issue about the MPC problem is to introduce the system constraints. For the defined ACC problem, the constraints are collected under objective constraint and state constraints. The objective constraints are

$$d \geq d_0 \tag{18}$$

and the system constraints are,

$$\begin{aligned} v_{\max} &\geq v \geq v_{\min} \\ a_{\max} &\geq a \geq a_{\min} \\ j_{\max} &\geq j \geq j_{\min} \end{aligned} \tag{19}$$

The constraints defining the inter-vehicle distance and the speed of the ACC vehicle are the prerequisites of the problem while the constraints over the acceleration and jerk can be considered as design parameters that describe the comfort performance of the ACC vehicle.

D. MPC formulaton

Defined cost function subjected to state and objective constraints are formulized as quadratic programming (QP) which is solved in real time for each time step. Furthermore, all system and objective constraints can be gathered in a matrix M, and the boundaries in a vector γ. In other words,

$$\min\left\{ \underset{U(N_c)}{J} (u(N_c), x(N_p)) \right\}$$

$$\text{such that } MU(N_c) \leq \gamma \tag{20}$$

QP formulation is solved for each time step and only the first value of the control vector corresponding to the actual time step is applied to the system. The control vector is used also to predict the future step in the prediction model. Until the next step, the calculated control signal is valid and is considered as the desired acceleration by the low- level throttle and brake controllers.

Optimized control value is considered as the ACC vehicle's desired acceleration or deceleration value for the low level control. Using this value and the actual ACC vehicle acceleration value, low level control generates a throttle or brake output with a closed-loop feedback structure.

IV. SIMULATIONS

The numerical values related to the control system are presented in Table 1 and are based on the previous works in the literature [1]. The weighting matrices are shaped qualitatively such that, spacing error and relative velocities have larger and equivalent importance with respect to acceleration and jerk of the ACC vehicle. The designed control system is tested under different traffic scenarios based on the lateral and longitudinal maneuvers of the preceding vehicle or ACC equipped vehicle. During simulations, gear selections are made autonomously by the automatic gear selection map governed by vehicle speeds as described in the modeling section. The gear changing procedure is kept independent from the control structure.

First scenario aims to simulate the case when ACC equipped vehicle cruises with a constant speed set by the driver (cruise control mode), detects a preceding vehicle with a speed lower than its cruise control speed. The initial distance between the vehicles is set to 100 m at the beginning of the simulation. The cruise speed of the ACC vehicle and the preceding vehicle are 20 m/s and 10 m/s respectively.

In Figure 4, we can see the velocity profile of the ACC and target vehicles. In Figure 5, the inter-vehicle distance can be seen. The distance at the end of the simulation is 20 m, which is the desired distance for T_h = 1.5 s, V_{front} = 10 m/s and d_0 = 5m.

TABLE I. CONTROL PARAMETERS

Control Parameters		
Parameter	***Symbol***	***Numerical Values***
Prediction Horizon	N_p	10
Control Horizon	N_c	5
Min. acceleration limit	a_{min}	-5 m/s^2
Max. acceleration limit	a_{max}	2 m/s^2
Min. jerk limit	j_{min}	-5 m/s^3
Max. jerk limit	j_{max}	2 m/s^3
Stopping distance	d_0	5 m
Min. ACC vehicle speed	V_{min}	0 m/s
Max. ACC vehicle speed	V_{max}	30 m/s

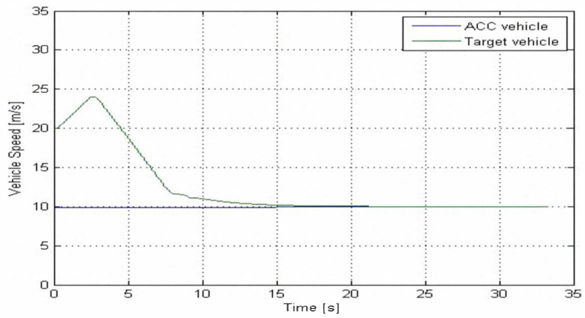

Figure 4. Vehicle speed for scenario 1

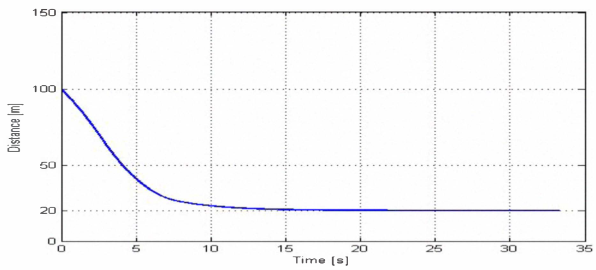

Figure 5. Inter-vehicle distance

From the simulation solutions, an overshoot of the ACC vehicle which exceeds the cruise speed that is the desired speed defined by the driver. For Scenario 1, the results show that this limit is passed over to regulate the inter-vehicle distance at the early stage of the following. To prevent this overshoot, either the weighting parameters of the $\boldsymbol{Q}$ matrix can be adjusted or a more precisely a decision logic can be implemented to disregard the desired acceleration values which would bring the ACC vehicle over the cruise control limit.

In Figure 6, the desired acceleration calculated by the higher level MPC controller and the actual acceleration controlled by the lower level throttle and brake controllers are plotted. The acceleration and deceleration values of the MPC remain in predefined limits.

The lower controllers performance exhibits a good tracking of the desired acceleration generated by the MPC. Since the higher level controller sampling time is larger than the lower control, desired acceleration level is kept constant during one step of the MPC operation cycle.

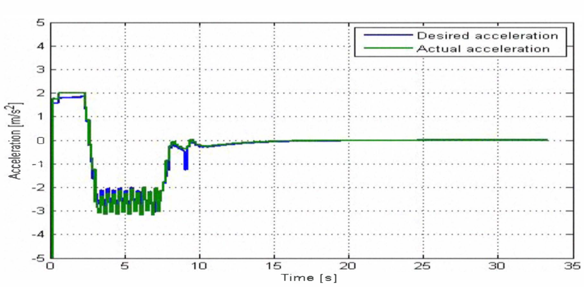

Figure 6. MPC output and actual accelerations

Second scenario simulates the situation when the preceding vehicle accelerates during a following condition. In Figure 7, speeds of each vehicle and inter-vehicle distance are seen. For this scenario, the ACC speed and the target speed are 30 m/s and 20 m/s respectively and the initial inter vehicle distance is 180 m. Until the distance enters the detection limit which is 150 m, ACC vehicle is stayed in cruise control mode.

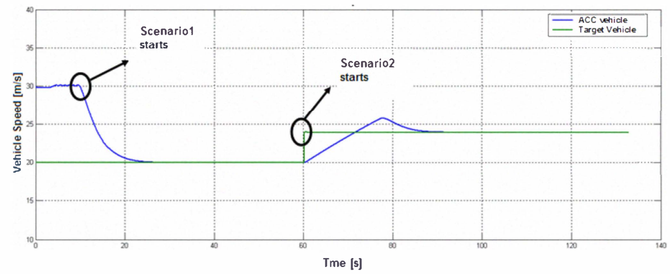

Figure 7. Vehicle speeds for scenario 2

The adaptation of the vehicle speed of ACC vehicle and the starting moments of the scenarios are illustrated. Since there is no acceleration limit for the target vehicle, a sudden speed changes occurs, however ACC vehicle acceleration remains within the defined limits. Furthermore, the exceedance of the ACC vehicle speed over the cruise speed is prevented through a logic mechanism.

For this scenario, the time gap is selected arbitrarily 2 s. The inter-vehicle distance and the desired distance are seen in Figure 8.

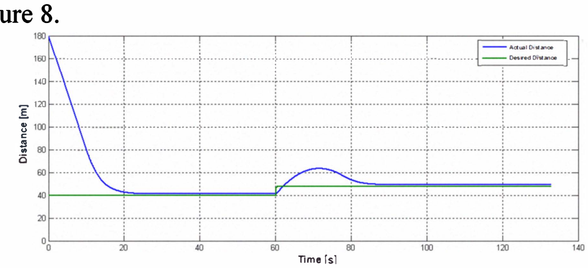

Figure 8. Intervehicle distance and desired distance for Scenario 2

The third scenario which will be presented in this paper is the interaction of the third vehicle during a pursuit. After the ACC vehicle speed is adapted to a target vehicle which is in cruise mode, a third vehicle is entered between the vehicles with the same speed and the ACC vehicle regulates its speed to adjust the inter-vehicle distance. In Figure 9 and Figure 10, the speed of the vehicles and the distances can be seen.

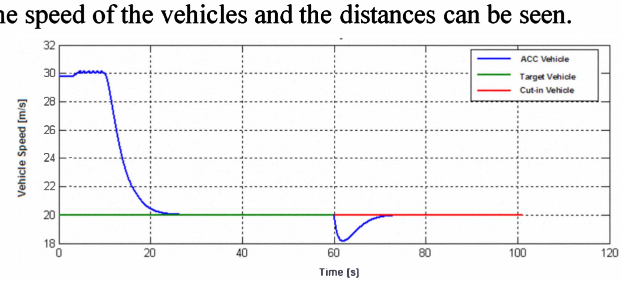

Figure 9. Vehicle speeds for scenario 3

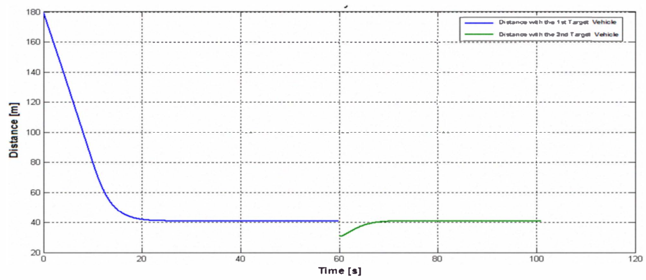

Figure 10. Inter-vehicle distances for scenario 3

Some other generic traffic scenarios like lane-changes and stop and go maneuvers can also be distinguished by the control mechanism. For the lack of space, only those three scenarios are presented here.

V. CONCLUSION

In this paper, MPC based control scheme is designed to solve the ACC problem. The designed controller is adapted to a nonlinear vehicle model and several traffic scenarios are simulated, where the MPC scheme operates in a high level hierarchy while the actuation of throttle and brake commands are executed through dedicated low level controllers. In each presented scenarios, the MPC scheme generates satisfactory desired acceleration and deceleration commands that guarantee the required inter-vehicle distance and zero relative speed of the ACC problem.

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