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Real-time adaptive cruise controller with neural network model trained by multi-objective model predictive controller data

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ABSTRACT

In this paper, an adaptive cruise control system is designed that is controlled by a neural network model. This neural network model is trained with data resulting from the simulation of a multi-objective adaptive cruise control system. For this purpose, first, an adaptive cruise control system was designed using the concept of model predictive control to maintain the desired speed of the driver, maintain a safe distance with the car in front, reduce fuel consumption and increase ride comfort. Due to the time-consuming computations in predictive control systems and the consequent need for powerful and expensive hardware, it was decided to use the extracted data from the simulation of this designed cruise control system to train a neural network model and use this model to achieve control objectives instead of the predictive controller. Using the neural network model in the cruise control system, despite a significant reduction in computation time, the control objectives were well achieved, and in fact the model predictive controller accuracy and the neural network controller speed is combined.

1. Introduction

One of the most important driver assistance systems in the car is the adaptive cruise control system. The cruise control system was initially designed and used only to maintain the driver's desired speed. To solve the safety problem that occurred due to the lack of distance between the car with cruise control and the car or obstacles in front of it, the adaptive cruise control system was introduced that in addition to maintaining the desired speed of the driver, also considers the distance from the car or obstacles in front. If the distance to the front car or obstacle is less than the safe distance, the objective of maintaining the safe distance takes precedence over the objective of maintaining the desired speed. Today, in addition to these two primary objectives of the adaptive cruise control system, i.e. maintaining the desired speed and maintaining the safe distance, secondary objectives such as reducing fuel consumption and increasing ride comfort are also considered. Achieving all of these control objectives together requires a sophisticated control system that is constantly optimizing an objective function consisting of control objectives. For this purpose, different controllers or a combination of them have been used. So far, cruise control systems have been designed that in addition to maintaining the desired driver speed and maintaining the safe distance, aim to reduce fuel consumption [1-5], increase ride comfort [6], or both to reduce fuel consumption and increase ride comfort [7-10]. The model predictive controller has been used the most among controllers in multi-objective adaptive cruise

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control systems, and researchers have obtained very good results from this controller; but the model predictive controller, along with many advantages, has relatively long computational time. Regardless of the type of controller, reducing computation time due to increased controller usability and the possibility of using it in cheaper hardware has always encouraged researchers to find ways to reduce controller decision-making time or design controllers with short computation time. One of the controllers that has relatively short decision time is the neural network controller. The use of neural networks to control the car and especially the adaptive cruise control system is one of the most popular topics and various researchers have used neural networks for different purposes in the car. Ghaffari et al. used a neural network to predict the future behavior of a car equipped with a stop/go cruise control based on actual traffic data [11]. Marzbanrad and Moghaddam used a combination of genetic algorithms and neural networks to predict vehicle acceleration [12]. Ghaffari et al. presented a method based on artificial neural network for the calibration of an inertial accelerometer applied in the vehicle navigation. Levenberg-Marquardt algorithm is used to train the designed neural network [13]. Kazemi and Abdollahzade developed an adaptive technique for car following modeling in a traffic flow. The proposed technique includes an online fuzzy neural network which is able to adapt its rule-consequent parameters to the time-varying processes [14]. Fotouhi et al. predicted the vehicle's velocity time series using neural networks. A multi-layer perceptron network is designed for driving time series [15]. Colombaroni and Fusco used neural networks to model driver behavior in car following [16]. Kuyumcu and Sengor used neural networks to find the throttle valve opening in adaptive cruise control system [17]. Using driver behavioral data, Wang et al. developed a neural network model and used it to make decisions about the sudden entry or exit of the opposite vehicle in the electric vehicle cruise control system [18]. Huang et al. used neural networks to approximate unknown vehicle dynamics in the car platoon [19]. Lin et al. used a neuro-fuzzy controller to design a cruise control system and they considered the car model to be a very simple linear model [20]. Lin and Gwyn used a neuro-fuzzy controller in the Cooperative Cruise Control System (CACC) [21]. Some researchers have also designed multi-objective cruise control systems using neural networks. Lin et al. compared two adaptive cruise control systems that used MPC and DRL in an electric vehicle. They used a simple car model. Reducing energy consumption was one of the objectives, but increasing comfort did not consider [22]. Cherian and Sathiyan used the neural network model to increase comfort in adaptive cruise control, but reducing fuel consumption was not one of the objectives [23]. Using RBFN, Yoon and Jeon predicted the future behavior of the vehicle and used it in the adaptive cruise control system. Increasing comfort was one of the objectives of this system, but reducing fuel consumption was not one of the objectives [24]. Nie et al. designed a cruise control system with adaptive PID control with RBFN, which increasing safety was one of the objectives, but the reduction of fuel consumption was not one of control objectives [25]. Zhang et al. used the data of the MPC controller to train a neural network model and use it instead of the predictive controller in the adaptive cruise control system, which aimed to reduce fuel consumption but increase ride comfort has not been as one of control objectives [26].

The purpose of this study is to use the excellent capability of the model predictive controller to achieve control objectives and meet control constraints while reducing computational time. For this purpose, a multi-objective cruise control system was designed with the objectives of maintaining the desired speed, maintaining the safe distance, reducing fuel consumption, and increasing ride comfort using a predictive control strategy. The results showed that achieving the control objectives while meeting the control constraints was very desirable, but as mentioned, the implementation of this control system requires relatively powerful hardware to solve complex optimization equations in a fraction of a second in presence of constraints. To get rid of time-consuming calculations and achieve real-time control, the results of the multi-objective predictive cruise control simulation performed in MATLAB software were used to train a neural network model to be used instead of predictive controller. The result is the achievement of control objectives with

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appropriate accuracy along with a significant reduction in computational time. By using neural network model, control objectives and constraints are suitably met and a significant reduction in computational time makes it possible to use this cruise control system with a wide range of hardware.

2. Methods

In this study, first, a multi-objective predictive adaptive cruise control system was designed with the objectives of maintaining speed, maintaining safe distance, reducing fuel consumption, and increasing comfort. This cruise control system consists of upper-level and lower-level controllers. The upper-level controller is a model predictive controller that calculates the desired acceleration to achieve the control objectives in the presence of constraints and announces calculated acceleration to the lower-level controller. The lower-level controller calculates the amount of throttle valve opening or braking pressure required by the vehicle to achieve this desired acceleration. The predictive controller minimizes an objective function which includes the objectives of maintaining the desired speed of the driver, maintaining a safe distance from the vehicle in front, increasing ride comfort, and reducing fuel consumption in the presence of a constraint to maintain a safe distance at all times and also an acceleration constraint which is a maximum of $3\frac{\mathrm{m}}{\mathrm{s}^2}$ and a minimum of $-3\frac{\mathrm{m}}{\mathrm{s}^2}$. Acceleration limits has been selected to create ride comfort and avoid increasing travel time [27]. Then, by simulation in MATLAB software, this cruise controller was used in a car (so-called host car) moving behind another car (so-called preceding car), and the data of distance, speed, acceleration, throttle valve opening, and brake pressure saved; Finally, these data were used to train a neural network model and that model used in the cruise control system instead of upper-level and lower-level controllers.

2.1. Longitudinal model of the car

Modeling of car longitudinal dynamics consists of two main approaches, which are: car dynamics in general and car subsystem dynamics. The car consists of many subsystems and the most important parts for analyzing and modeling the longitudinal dynamics of the car are: engine, torque converter, transmission, final drive, and wheels. If we look at the car from the outside as a free body as shown in Figure 1, forces such as gravity force, air resistance force, wheel longitudinal forces, and rolling resistance forces enter it.

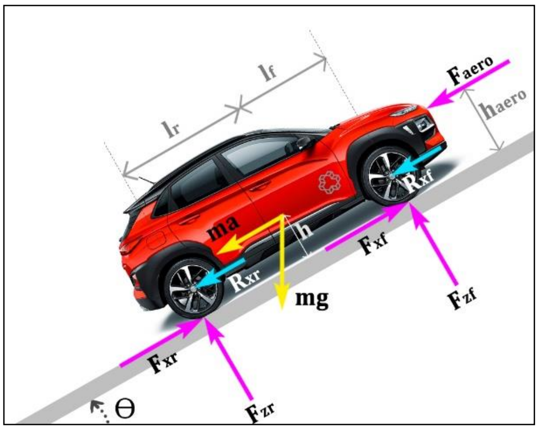

Figure 1. Forces on the vehicle

2.2. Control structure

The designed controller has a hierarchical structure that consists of two controllers called the upper-level controller and the lower-level controller. In each control step, the upper-level controller that is a model predictive controller, while minimizing a specific objective function in the presence of constraints calculates desired acceleration and announces it to the lower-level controller and lower-level controller which is also called longitudinal controller determines the amount of throttle valve opening or brake pressure required to achieve this acceleration.

This research consists of two main parts, the first part is car modeling and design of the controller and the second part is the use of simulation data of this controller to train a neural network model. Since the second part is considered as innovation of this paper, to avoid prolonging the discussion, deriving vehicle dynamic equations and control structure are described in the appendices of the paper.

2.3. Simulation of designed cruise control system

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The designed cruise control system is a cruise control system with upper-level and lower-level controllers. The objectives of the adaptive cruise control system are: maintain the desired speed, maintain the safe distance from the car in front, reduce fuel consumption, and increase ride comfort. In the predictive controller, in each control step, an optimization problem based on an objective function and some constraints were solved to calculate a control command. Optimal acceleration, calculated by the upper-level controller, is limited between the maximum of $3\frac{\mathrm{m}}{\mathrm{s}^2}$ and the minimum of $-3\frac{\mathrm{m}}{\mathrm{s}^2}$, and the desired driver speed is $30\frac{\mathrm{m}}{s}$ equals to $108\frac{\mathrm{km}}{\mathrm{h}}$. This adaptive cruise control system is used to control a nonlinear vehicle model in MATLAB software and the simulation results are shown in Figures 2 to 5.

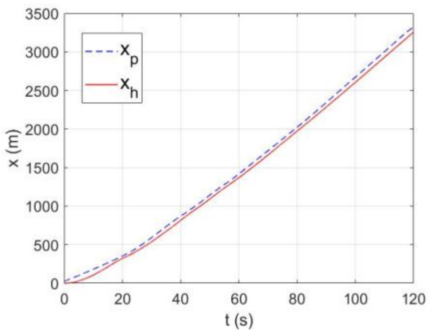

Figure 2. Position of two cars relative to each other

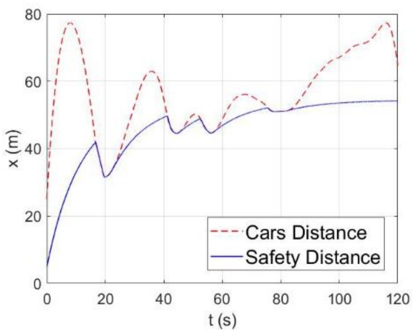

Figure 3. Distance between two cars compared to the safe distance

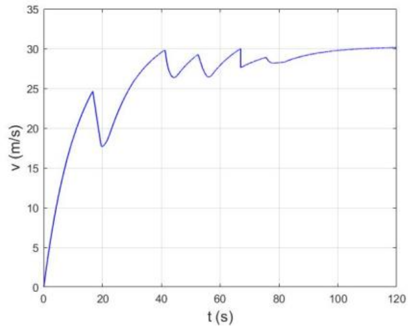

Figure 4. Host car speed

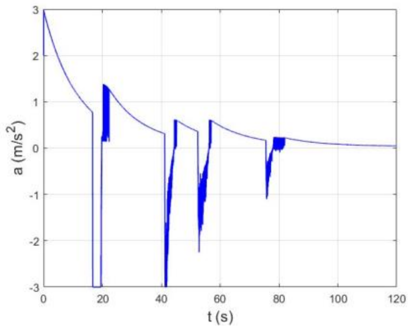

Figure 5. Host car acceleration

2.4. Train the neural network model

As can be seen in Figures 2 to 5, the results of using the designed adaptive cruise control system are very good, but since the calculations of the predictive controller and lower-level controller take a relatively long time, to make the multi-objective adaptive cruise control system usable in wider range of hardware, data from simulated cruise control systems used to train a neural network model. Then this trained model replaced the upper-level and lower-level controllers in the cruise control system. The neural network model has two hidden layers that each layer has 10 neurons. To determine the number of hidden layers and the number of neurons in each layer, different modes were selected and examined and finally, these values that had the best results were selected. Also, the Levenberg-Marquardt method has been used for backpropagation calculations; Because the Levenberg-Marquardt method has two choices in each iteration, it is more robust than a method such as Gradient Descent (GD) or Gauss-Newton (GN). It also has higher convergence speed and lower sensitivity to initial estimation rather than either GD or GN method [28]. To train the neural network model, the host vehicle speed and the distance between the host vehicle and the front vehicle were selected as inputs and the throttle valve opening and brake pressure were selected as outputs. This neural network model replaced the upper-level and lower-level controllers in adaptive cruise control system and the simulation results of using this neural network model are shown in Figures 6 to 9.

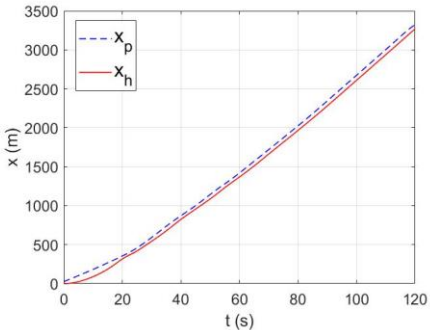

Figure 6. Position of two cars relative to each other using the neural network model

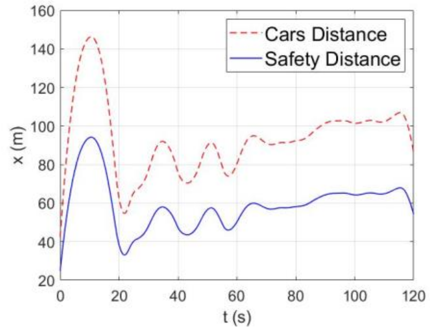

Figure 7. Distance between two cars compared to the safe distance using the neural network model

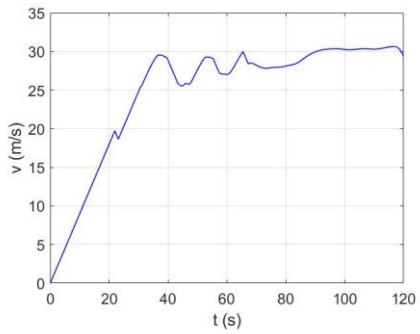

Figure 8. Host car speed using the neural network model

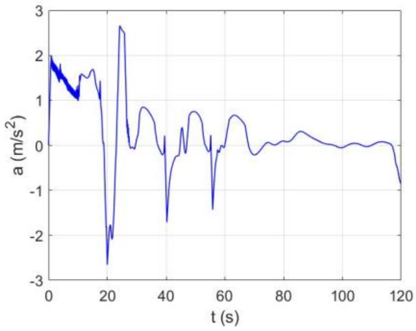

Figure 9. Car acceleration using the neural network model

3- Results

After training the neural network model, it was used to control a nonlinear vehicle model. In the simulations, the desired driver speed is assumed to be $30\frac{\mathrm{m}}{s}$ equivalent to $108\frac{\mathrm{km}}{\mathrm{h}}$. In the neural network model, the inputs are the host vehicle speed and the distance of the host vehicle from the front vehicle and the outputs are the throttle valve opening and brake pressure, and this model replaced the upper-level and lower-level controllers.

Figure 6 shows the position of the two cars relative to each other; As can be seen, the host car is always far from the preceding car. Figure 7 has a better expression of safety and shows the distance between two cars compared to the safe distance calculated by the controller; It can be seen that the distance between two cars is always greater than the safe distance calculated by the controller, which indicates full compliance with the safety constraint. Figure 8 is the host vehicle speed curve, which shows that the driver's desired speed of $30\frac{\mathrm{m}}{s}$ is well achieved and maintained. Figure 9 is the host vehicle acceleration curve, and can be seen that acceleration constraints, i.e. maximum of $3\frac{\mathrm{m}}{\mathrm{s}^2}$ and minimum of $-3\frac{\mathrm{m}}{\mathrm{s}^2}$ are well considered.

3.1. Comparison with PID controller

To observe the proper performance of the neural network controller, the results of its use are compared with the results of the use of the PID controller. The PID controller is adjusted with a lot of trial and error and has a relatively good response shown in Figures 10 to 13. Despite the relatively good results of the PID controller, these results are very poor compared to the results of the neural network controller. Safety criterion is not observed sometimes (for example, around the 20 second) and the desired speed is not well met. It is also clear from the acceleration curve that the acceleration constraints are not observed and jerk is very high. Fuel consumption is also almost 30% higher than the neural network controller. Therefore, the performance of the neural network controller is much better than a widely used controller such as a well-tuned PID, and in fact, the PID controller cannot be used here due to non-compliance with constraints and poor performance.

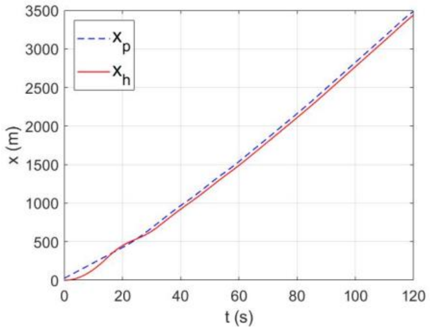

Figure 10. Position of two cars relative to each other using the PID controller

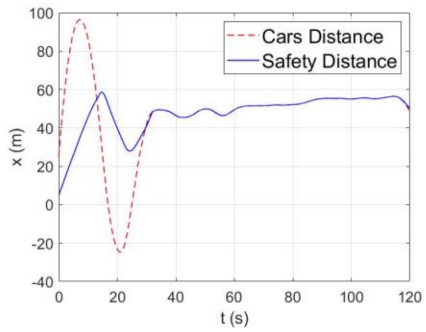

Figure 11. Distance between two cars compared to the safe distance using the PID controller

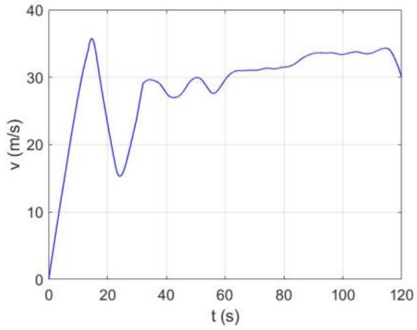

Figure 12. Host car speed using the PID controller

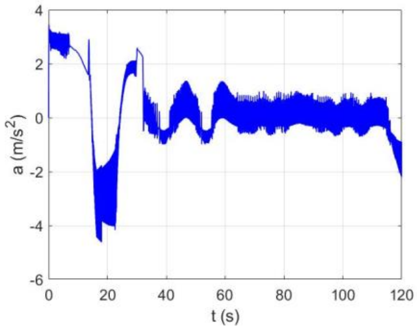

Figure 13. Host car acceleration using the PID controller

4 - Conclusion

Using the model predictive controller in a hierarchical control structure of a multi-objective adaptive cruise control system leads to excellent results, and its only drawback is the long computation time and the need for powerful hardware. So, the results of the simulation of this cruise control system were used to train a neural network model and it was used in the cruise control system. The trained model fully meets the safety criterion, which is to maintain the safe distance from the preceding car. Also, achieves and maintains the desired speed of the driver and maintains acceleration within the specified range. Therefore, in addition to achieving control objectives and meeting safety criterion, the computation time is greatly reduced and the possibility of using this multi-objective cruise control system in low-cost and not very powerful hardware is provided.

Appendix A: Control-oriented model

According to Figure 1, by writing the balance of external forces acting on the car along the longitudinal axis of the car according to Newton's second law we have:

$$F_{xf} + F_{xr} - mgsin\theta - F_{aero} - R_{xf} - R_{xr} = m\ddot{x} \quad \text{(A1)}$$

Where, F_{xf} is the sum of the longitudinal forces on the front wheels, F_{xr} is the sum of the longitudinal forces on the rear wheels, m is the mass of the car, g is the gravitational acceleration, θ is the angle of the road, F_{aero} is the aerodynamic force, R_{xf} is the sum of the rolling resistance forces on the front wheels and R_{xr} is the sum of the rolling resistance forces on the rear wheels of the car. The longitudinal forces of the wheels are the main forces for driving the car. The aerodynamic force can be expressed as follows:

$$F_{aero} = 0.5\rho C_d A_f (V_x \pm V_{wind}) \quad \text{(A2)}$$

Where, ρ is the air density, C_d is the air drag coefficient, A_f is the projected area of the front surface of the car, V_x is the longitudinal speed of the car and V_{wind} is the wind speed. The sum of the vertical forces acting on the front and rear wheels (F_{zf} and F_{zr}, respectively) can be calculated by writing the balance of forces around the point of contact of the wheels with the road:

$$F_{zf} = \frac{-F_{aero}h_{aero} - m\ddot{x}h - mghsin\theta + mglcos\theta}{l_f + l_r}$$

$$F_{zr} = \frac{F_{aero}h_{aero} + m\ddot{x}h + mghsin\theta + mglcos\theta}{l_f + l_r} \quad \text{(A3)}$$

Where, l is the length of the car, h_{aero} is the distance of the aerodynamic force from the ground level, and l_f, l_r and h are the distance of the center of gravity of the car from the front axle, rear axle, and ground level, respectively. Rolling resistance is usually defined as a function of the sum of the vertical forces acting on the wheels:

$$R_{xf} + R_{xr} = f(F_{zf} + F_{zr}) = fmgcos\theta \quad \text{(A4)}$$

Where, f is the coefficient of rolling resistance. The longitudinal forces acting on the wheels can be calculated from the following equations:

$$F_{xf} = \mu F_{zf}$$
$$F_{xr} = \mu F_{zr} \quad \text{(A5)}$$

Where, μ is the coefficient of friction of the wheel with the road. To calculate the coefficient of friction of the wheel with the road, the nonlinear model of Pacejka has been used:

$$\mu = Dsin[Ctg^{-1}\{B\sigma_x - E(B\sigma_x - tg^{-1}B\sigma_x)\}] \quad \text{(A6)}$$

Where, σ_x is the wheel slip ratio and B, C, D, and E are the pacejka coefficients, which indicate the stiffness coefficient, shape coefficient, maximum value, and curvature coefficient of the coefficient of friction, respectively. In the following, dynamic equations related to car subsystems and their relationship with each other are presented. For the engine can be written:

$$I_e\dot{\omega}_e = T_i - T_f - T_a - T_p \quad \text{(A7)}$$

Where, I_e is engine moment of inertia, $\dot{\omega}_e$ is engine angular acceleration, T_i is torque resulting from combustion in the engine, T_f is the torque due to friction, T_a is torque consumed by equipment, and T_p is pump torque and expresses load from the pump on the engine. If we call T_i - T_f - T_a the net torque produced by the engine and display it with T_e, we can write:

$$I_e\dot{\omega}_e = T_e - T_p \quad \text{(A8)}$$

The torque converter is modeled as follows:

$$T_p = T_t = -0.0067644\omega_p^2 + 0.0320024\omega_p\omega_t - 0.0252441\omega_t^2 \quad \text{(A9)}$$

Where, T_t is the turbine torque, ω_p is the pump angular speed and ω_t is the turbine angular speed. The wheels angular speed is affected by the dynamics of the car subsystems from the engine to the wheel. The wheel angular speed is the angular speed of the turbine divided by the product of gearbox ratio and final drive ratio:

$$\omega_w = \frac{1}{R}\omega_t \quad \text{(A10)}$$

Where, ω_w is the wheel angular speed and R is the product of gearbox ratio and final drive ratio. For driving wheels (for example, front wheels in front-wheel-drive cars) it can be written:

$$I_w\dot{\omega}_{wf} = T_{wheel} - r_{eff}F_{xf} \quad \text{(A11)}$$

And for driven wheels it can be written:

$$I_w\dot{\omega}_{wr} = -r_{eff}F_{xr} \quad \text{(A12)}$$

Where, I_w is wheel moment of inertia, r_{eff} is wheel effective radius and T_{wheel} is wheel torque.

As mentioned earlier, the upper-level controller calculates an optimal acceleration (a_{des}) and announces it to the lower-level controller. lower-level controller tries to realize the following relation:

$$\ddot{x} = \ddot{x}_{des} \quad \text{(A13)}$$

Then, it calculates the torque required to achieve this desired acceleration. To calculate the torque, assume that the torque converter is locked and no

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slippage occurs between the wheels and the road. These two assumptions are reasonable because the cruise control system is usually used in gear 3 and above that in those cases the torque converter is locked; Also due to smooth driving when using the cruise control system, the wheel's slip is about zero. If the torque converter is locked and the gearbox is in the steady state (i.e. not shifting gears) and the longitudinal slip of the wheels is negligible, we can relate the angular velocity of the wheels to the angular velocity of engine with the following relation:

$$\omega_w = \frac{1}{R}\omega_e \tag{A14}$$

By combining the above equations, we will have:

$$T_e = \frac{J_e R}{r_{eff}}\ddot{x}_{des} + \frac{r_{eff}}{R}R_x + 0.5\rho C_d A_f \frac{r_{eff}^3}{R^3}\omega_e^2 + \frac{T_{br}}{R} \tag{A15}$$

Now, having the angular velocity of the engine and the desired engine torque and using the engine map, the amount of throttle opening required to achieve the desired acceleration can be determined. The engine map is shown in Figure A1 which gives the throttle angle in terms of engine torque and angular velocity of engine.
The parameters of the developed model are given in Table A1.

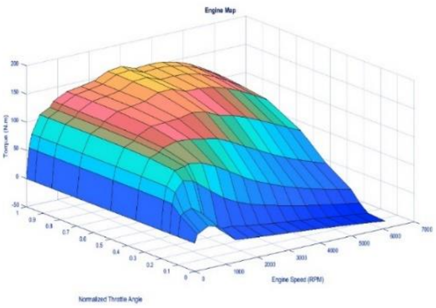

Figure A1. Engine Map

Table A1. Car Model parameters

parameter	unit	value
car effective aria	m^2	2.1
air drag coefficient	-	0.35
aerodynamic force distance from the ground	m	0.54
wheel moment of inertia	$kg.m^2$	0.318
final drive moment of inertia	$kg.m^2$	0.01
engine moment of inertia	$kg.m^2$	0.25
wheelbase	m	2.415
distance of car CG from front axle, rear axle, and ground	m	h=0.54 l_f=0.955 l_r=1.460
car mass	kg	1415
wheel effective radius	m	0.279
final drive ratio	-	3.9
air density	$kg.m^{-3}$	1.206

Appendix B: Control structure

The control structure for design of this multi-objective cruise control system (maintaining speed, maintaining a safe distance, reducing fuel consumption and increasing comfort) is a hierarchical control structure with an upper-level controller, that calculates the optimal acceleration to meet the control objectives in the presence of the constraints and announces that acceleration to the lower-level controller and so the lower-level controller calculates the amount of throttle valve opening or braking pressure required to achieve this desired acceleration. Due to the function of the upper-level controller, which actually includes multi-objective optimization, and the power of the model predictive controller (MPC) to perform control operations based on optimization in the presence of various constraints, the upper-level controller is a model predictive controller. In each control step, the model predictive controller obtains values for acceleration in the presence of constraints and minimizing a specific objective function.

A model that also called the process model is used to predict the future outputs of the process based on past and present values and taking into account the calculated optimal future control commands. The control commands are calculated by the optimizer taking into account the objective function (in which the future tracking error is included) as well as the constraints. The process model plays an important role in the model predictive controller and should be able to describe process dynamics to predict future outputs. System state-space equations can be written as follows:

$$\begin{aligned} x(t) &= Ax(t-1) + Bu(t-1) \\ y(t) &= Cx(t) \end{aligned} \tag{B1}$$

Where A is the system matrix, B is the input matrix and C is the output matrix. These equations can be used to predict system outputs at later times. The predicted outputs will be as follows [30]:

$$\begin{aligned} &\hat{y}(t+k \mid t) = \\ &C\hat{x}(t+k \mid t) = \\ &C[A^k x(t) + \sum_{i=1}^{k} A^{i-1} Bu(t+k-i \mid t)] \end{aligned} \tag{B2}$$

The control variable u must be found such that the following objective function:

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$$J = \sum_{j=1}^{N} \alpha(j)[\hat{y}(t+j\,|\,t) - w(t+j)]^2 + \sum_{j=1}^{N_c} \beta(j)[u(t+j-1)]^2 + \sum_{j=1}^{N_c} \gamma(j)[\Delta u(t+j-1)]^2 \quad \text{(B3)}$$

In the presence of the following constraints:

$$\begin{aligned} &\forall t: \\ &u_{\min} \le u(t) \le u_{\max} \\ &du_{\min} \le u(t) - u(t-1) \le du_{\max} \\ &y_{\min} \le y(t) \le y_{\max} \end{aligned} \quad \text{(B4)}$$

Be minimized. α, β and γ are the weights we assign to each term of the objective function, and w is the reference vector for the system outputs. In designing the upper-level controller, we encounter a system that its state variables are: distance of the host vehicle from the vehicle in front (x_p-x_h), speed of the host vehicle (v_h) and acceleration of the host vehicle (a_h). Also, system measured outputs are: distance of two vehicles from each other (x_p-x_h) which is measured by radar and speed of the host vehicle (v_h) which is measured by the speed sensor of the host vehicle. The front vehicle velocity (v_p) enters into the system equations as a disturbance. The control variable is the desired acceleration (a_{des}) that will be sent to the lower-level controller. Due to its complex dynamics, the car achieves its acceleration (a) to this desired acceleration (a_{des}) after a time delay that is called time constant. relation between desired acceleration and actual acceleration can be expressed according to the following equation:

$$\ddot{x} = \frac{1}{\tau s + 1} \ddot{x}_{des} \quad \text{(B5)}$$

And in other words:

$$\tau \dddot{x} + \ddot{x} = \ddot{x}_{des} \quad \text{(B6)}$$

Where x is the longitudinal position of the vehicle and τ is the delay or time constant. Therefore, considering the upper-level controller, the state variables are:

$$X = \begin{bmatrix} x_p - x_h \\ v_h \\ a_h \end{bmatrix} \quad \text{(B7)}$$

And output variables are:

$$\begin{aligned} Y(1) &= x_p - x_h = X(1) \\ Y(2) &= v_h = X(2) \end{aligned} \quad \text{(B8)}$$

And control variable is:

$$U = a_{des} \quad \text{(B9)}$$

And the system state-space equations will be as follows:

$$\begin{aligned} \frac{dX}{dt}(1) &= v_p - v_h \\ \frac{dX}{dt}(2) &= a_h \\ \frac{dX}{dt}(3) &= -\frac{1}{\tau} a_h + \frac{1}{\tau} a_{des} \end{aligned} \quad \text{(B10)}$$

It is assumed that the measurement of vehicle speed and distance between two vehicles has noise, so an extended Kalman filter is used to obtain all state variables. The Kalman filter is an optimal estimator and is used when it is not possible (or cost-effective) to measure all the state variables or the measurement of the variables has noise.

The safe distance from the car in front is described as a variable which is obtained from the following equation:

$$d = d_0 + t_{gap} v_h \quad \text{(B11)}$$

Where d is the expected safe distance, d_0 is the minimum safe distance that here is 5 meters, t_{gap} is the time distance that here is 1.5 seconds, and v_h is the speed of the host vehicle. The time distance is the time it takes for the rear car to reach the current position of the front car. To achieve the objectives of increasing comfort and decreasing fuel consumption, the amount of positive and negative acceleration and jerk are limited and included in the objective function. For this purpose, the desired acceleration calculated by the upper-level controller is limited between $-3\frac{m}{s^2}$ and $3\frac{m}{s^2}$ and the derivative of this acceleration (jerk) is limited between $-2\frac{m}{s^3}$ and $2\frac{m}{s^3}$. In the objective function, a weight is considered for each objective, which

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expresses the value of achieving that objective compared to other objectives. The objective function is as follows:

$$J = w_1 a_{des}^2 + w_2 j^2 + w_3 (d - (x_p - x_h))^2 + w_4 (v_{ref} - v_h)^2 \quad \text{(B12)}$$

In which, while maintaining the desired speed of the driver and maintaining a safe distance, an effort has been made to limit acceleration and jerk in order to reduce fuel consumption and increase comfort. Because limiting the sudden change of speeds (acceleration) and the sudden change of accelerations (jerk) has a severe effect on reducing fuel consumption and increasing comfort. The Control constraints are as follows:

$$\begin{aligned} & d \le x_p - x_h \\ & 0 \le v_h \le 60 \\ & -3\, m/s^2 \le a_{des} \le 3\, m/s^2 \\ & -2\, m/s^2 \le j_{des} \le 2\, m/s^2 \end{aligned} \quad \text{(B13)}$$

After calculating the desired acceleration by the upper-level controller, the car must reach its acceleration to this desired acceleration. This task is performed by the lower-level controller. The lower-level controller calculates the amount of throttle valve opening or the amount of brake pressure required to achieve this acceleration. For the lower-level controller, the dynamic equations of the vehicle derived in Appendix A is used. According to the objectives of reducing fuel consumption and increasing comfort, when it is necessary to reduce acceleration, if the safety criterion is maintained, closing the throttle valve is prior to braking. In the Appendix A, using Newton's second law and the dynamic equations of various parts of the car and their interactions, the relation between desired acceleration and engine torque was obtained:

$$T_e = \frac{J_e R}{r_{eff}} a_{des} + \frac{r_{eff}}{R} R_x + 0.5 \rho C_d A_f \frac{r_{eff}^3}{R^3} \omega_e^2 + \frac{T_{br}}{R} \quad \text{(B14)}$$

In other words, the upper-level controller calculates the desired acceleration (a_{des}) and announces it to the lower-level controller, and in the lower-level controller using the above equation, the engine torque required to reach the car to this acceleration is calculated and then having torque and angular velocity of the engine and using the engine map, which is the relation between the three variables of engine torque, engine angular velocity and the amount of throttle valve opening, the amount of throttle valve opening is calculated to achieve the desired acceleration. In the above equation, in the case where the calculated desired acceleration is positive, we consider the braking torque (T_{br}) to be zero to calculate the engine torque, and in the case where the calculated desired acceleration is negative, we consider the engine torque (T_e) to be zero to calculate the braking torque.

Nomenclature:

F_{xf}	sum of the longitudinal forces on the front wheels
F_{xr}	sum of the longitudinal forces on the rear wheels
m	mass of the car
g	gravitational acceleration
θ	angle of inclination of the road
F_{aero}	aerodynamic force
R_{xf}	sum of the rolling resistance forces on the front wheels
R_{xr}	sum of the rolling resistance forces on the rear wheels
ρ	air density
C_d	coefficient of air drag
A_f	projected area of the front surface of the car
V_x	longitudinal speed of the car
V_{wind}	wind speed
F_{zf}	sum of the vertical forces acting on the front wheels
F_{zr}	sum of the vertical forces acting on the rear wheels
l	length of the car
h_{aero}	distance of the aerodynamic force from the ground level
l_f	distance of the center of gravity of the car from the front axle

l_r	distance of the center of gravity of the car from the rear axle
h	distance of the center of gravity of the car from ground level
R_{xf}	sum of the rolling resistance forces on the front wheels
R_{xr}	sum of the rolling resistance forces on the rear wheels
f	coefficient of rolling resistance
F_{xf}	sum of the longitudinal forces on the front wheels
F_{xr}	sum of the longitudinal forces on the rear wheels
μ	coefficient of friction of the wheel with the road
σ_x	wheel slip ratio
B	stiffness coefficient of the coefficient of friction
C	shape coefficient of the coefficient of friction
D	maximum value of the coefficient of friction
E	curvature coefficient of the coefficient of friction
I_e	engine moment of inertia
$\dot{\omega}_e$	engine angular acceleration
T_i	torque resulting from combustion in the engine
T_f	torque due to friction
T_a	torque consumed by the equipment
T_p	pump torque
T_e	net torque produced by the engine
T_t	turbine torque
ω_p	pump angular speed
ω_t	turbine angular speed
ω_w	wheel angular speed
R	product of gearbox ratio and final drive ratio
I_w	wheel moment of inertia
r_{eff}	wheel effective radius
T_{wheel}	wheel torque

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