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Research Article

Model Predictive Control of a Plug-In Hybrid Electric Vehicle's Cruise Control System

Mario Barnard* and Mohamed Zohdy

Department of Electrical and Computer Engineering, Oakland University, Rochester, MI, USA

***Corresponding Author:** Mario Barnard, Department of Electrical and Computer Engineering, Oakland University, Rochester, MI, USA.

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Abstract

In this paper, a Plug-In Hybrid Electric Vehicle's conventional cruise control system was modelled and improved using Model Predictive Control (MPC). Both a linear MPC and nonlinear MPC was modelled for comparison of the control of the cruise control's system.

Keywords: Model Predictive Control (MPC), Nonlinear Model Predictive Control, Automotive, Cruise Control, Conventional Cruise Control, Plug-In Hybrid Electric Vehicle (PHEV)

Introduction

As Plug-in Hybrid Electric Vehicles (PHEVs) are becoming more common in auto manufacturers product line-ups, more robust control strategies will be needed for these complex vehicles. PHEVs also use cruise control as conventional automobiles do. PHEVs can either be equipped with conventional cruise or adaptive cruise control (ACC). This paper focuses on the conventional cruise control system using Model Predictive Control (MPC). The control strategy is to use a linear model predictive controller, then use the same model with the nonlinear model predictive controller replacing the linear model predictive controller. The Chrysler Pacific Hybrid will be used as a basis for this paper.

Overview of automotive cruise control systems

Automatic cruise control is an excellent example of a feedback control system found in many modern vehicles. The purpose of the cruise control system is to maintain a constant vehicle speed despite external disturbances, such as changes in wind or road grade. This is accomplished by measuring the vehicle speed, comparing it to the desired or reference speed, and automatically adjusting the throttle according to a control law [1].

Fiat Chrysler Automobiles also uses the term "Speed Control" for "Cruise Control". When engaged, the Speed Control takes over accelerator operations at speeds greater than 25 mph (40 km/h). The Speed Control buttons are located on the right side of the steering wheel. In order to ensure proper operation, the Speed Control System has been designed to shut down if multiple Speed Control functions are operated at the same time. If this occurs, the Speed Control System can be reactivated by pushing the Speed Control on/off button and resetting the desired vehicle set speed. To activate, push the on/off button to activate the Speed Control. The cruise indicator light in the instrument cluster display will illuminate. To turn the system off, push the on/off button a second time. The cruise indicator light will turn off. The system should be turned off when not in use. In order to set a desired speed, turn the Speed Control on. The vehicle should be traveling at a steady speed and on level ground before pushing the SET (+) or SET (-) button. When the vehicle has reached the desired speed, push the SET (+) or SET (-) button and release. Release the accelerator and the vehicle will operate at the selected speed. In order to vary the speed setting to increase speed, one can increase speed by pushing the SET (+) button. The speed increment shown is dependent on the chosen speed unit of U.S. (mph) or Metric (km/h). For U.S. Speed (mph) units: pushing the SET (+) button once will result in a 1 mph increase in set speed. Each subsequent tap of the button results in an increase of 1 mph. If the button is continually pushed, the set speed will continue to increase until the button is released, then the new set speed will be established. In order to vary the speed setting to decrease speed, one can decrease speed by pushing the SET (-) button.

For U.S. Speed (mph) units: pushing the SET (-) button once will result in a 1 mph decrease in set speed. Each subsequent tap of the button results in a decrease of 1 mph. If the button is continually pushed, the set speed will continue to decrease until the button is released, then the new set speed will be established. In order to accelerate for passing, press the accelerator as you would normally. When the pedal is released, the vehicle will return to the set speed. In order to resumea previously set speed, push the RES button and release. Resume can be used at any speed above 20 mph (32 km/h). For the layout of the Speed Control Button configuration on the steering wheel, please refer to Figure 1 below [2].

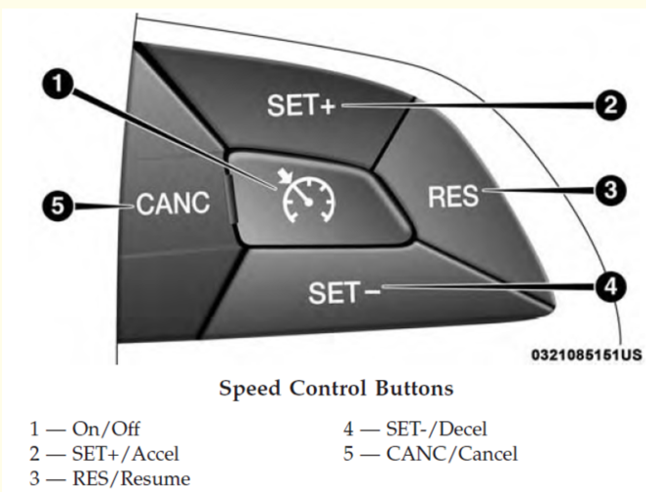

Figure 1: 2018 Chrysler Pacifica Steering Wheel Speed Control Buttons [2].

Cruise control can be dangerous when you cannot drive safely at a steady speed. Also, do not use your cruise control on winding roads or in heavy traffic. Cruise control may also be dangerous on slippery roads. On such roads, fast changes in tire traction can cause excessive wheel slip, and you could lose control [3].

Introduction to model predictive control (MPC)

Model Predictive Control (MPC) originated in the late 1970’s. Model Predictive Control does not designate a specific control strategy but rather an ample range of control methods that make explicit use of a model of the process to obtain the control signal by minimizing an objective function. The techniques that are employed by Model Predictive Control (MPC) are the explicit use of the model in order to predict the process output at future time instants or horizons, the control sequence calculation, objective function minimization, and the receding strategy [4].

One of the advantages of Model Predictive Control (MPC) is that it can be used to control a variety of processes from systems with simple dynamics to systems with complex dynamics. Model Predictive Control is able to control systems with long delay times or non-minimum or unstable phases. Model Predictive Control is able to handle multivariable systems as it intrinsically has compensation for dead times [4].

One of the disadvantages of Model Predictive Control (MPC) is that although the resulting control law is easy is to implement and requires little computation, its derivation is more complex than that of the classical PID controllers. If the system under investigation is a dynamic process, then the controller derivation can be computed in advance. If the system under investigation is an adaptive control case, then the controller derivation cannot be computed in advance and must be computed at every sampling time. If constraints are taken into account, then the computation time would increase. One must choose the appropriate process model [4].

Model Predictive Control (MPC) has proven to be a reasonable strategy for industrial control applications. The purpose of this paper is to provide another application that Model Predictive Control (MPC) can be used in the automotive industry.

All Model Predictive Control (MPC) algorithms possess common elements, and different options can be chosen for each element giving rise to different algorithms. These elements are prediction model, objective function, and obtaining the control law [4].

The continuous-time state-space representation of the Model Predictive Control algorithm is implemented as:

$\dot{\boldsymbol{x}}(t + 1) = A\mathbf{x}(t) + B\mathbf{u}(t)$--------- (1)

$\dot{\boldsymbol{y}}(t) = C\mathbf{x}(t) + D\mathbf{u}(t)$------------ (2)

where,

(t) = the state vector

(t) = the output vector

u(t) = the input or control vector

A = the state or system matrix (dimension)

B = the input matrix (dimension)

C = the output matrix (dimension)

D = the feedthrough or feedforward matrix (dimension)

The discrete-time state-space representation of the Model Predictive Control algorithm is implemented as [3]

$\dot{\boldsymbol{x}}(k + 1) = A\mathbf{x}(k) + B\mathbf{u}(k)$-------- (3)

$\dot{\boldsymbol{y}}(k) = C\mathbf{x}(k) + D\mathbf{u}(k)$-------- (4)

where,

(k) = the state vector

(k) = the output vector

u(k) = the input or control vector

A = the state or system matrix (dimension)

B = the input matrix (dimension)

C = the output matrix (dimension)

D = the feedthrough or feedforward matrix (dimension)

Common variables for Model Predictive Control (MPC)

Ts = Sample Time

P = Prediction Horizon

M = Control Horizon

In many cases, real processes are nonlinear, which means that that the system parameters depend on system states or/and time. Linearization is one possibility to map the system behavior into one invariant SS-system with the disadvantage of reduced model accuracy. Nonlinear system behavior can be represented by local model networks, which use in principle, local linearizations, in order to calculate the nonlinear system behavior [5].

Figure 2 shows the block diagram of the controller and plant of the system being observed.

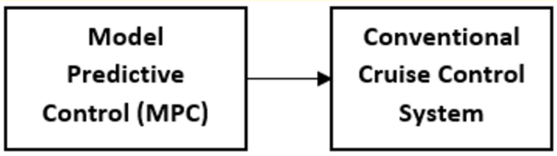

Figure 2: Block Diagram of the MPC Controller and Plant.

If the slope of the highway incline is considered, the vehicle must be equipped with an accelerometer. Highways are usually level and this may not need to be considered. This model has one type of disturbance. The disturbance that is included in the model is the road grade. A section of highway can have varying concrete. The road may have a combination of new and old sections of concrete depending on road repairs. In addition, road repair crews may just patch potholes or tar parts of the road instead of replacing a section. If these sections are uneven or are not smoothed down to match the existing section, then there would be bumps present which may affect the cruise control system.

Linear model predictive control (LMPC)

In this section, the plant is controlled with a Linear Model Predictive Controller (LMPC).

Figure 3 shows the block diagram of the Linear Model Predictive Control (LMPC) controller and plant of the system being observed. Figure 4A shows the model of LMPC control block and the plant. Figure 4B shows the transfer function of LMPC control block and the plant. Figure 4C shows the input and the output plots of the system.

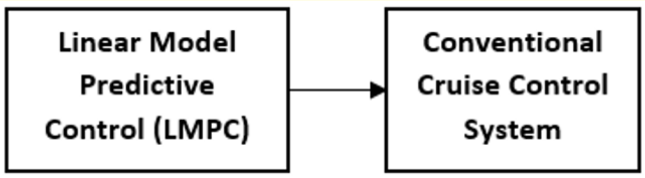

Figure 3: Block Diagram of the LMPC Controller and Plant.

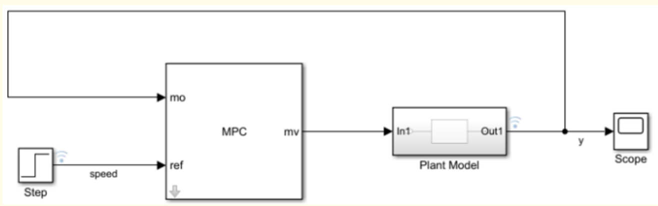

Figure 4A: Second Order LMPC Model.

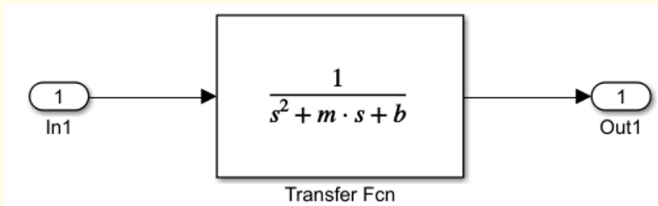

Figure 4B: Second Order LMPC Model.

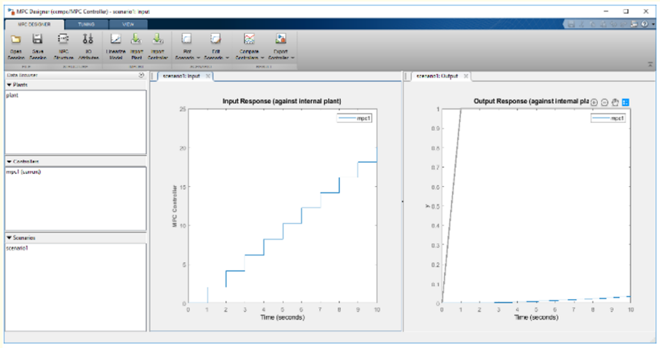

Figure 4C: Second Order LMPC Plot.

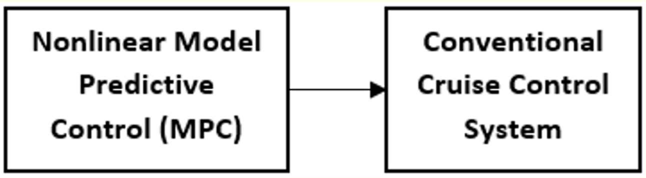

Figure 5: Block Diagram of the NLMPC Controller and Plant.

Nonlinear model predictive control (NLMPC)

In this section, the plant is controlled with a Nonlinear Model Predictive Controller.

Figure 5 shows the block diagram of the Nonlinear Model Predictive Control (NLMPC) controller and plant of the system being observed. Figure 6A shows the model of NLMPC control block and the plant. Figure 6B shows the transfer function of NLMPC control block and the plant. Figure 6C shows the input and the output plots of the system.

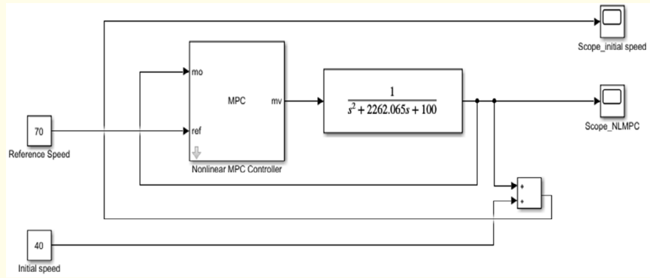

Figure 6A: Second Order NLMPC Model.

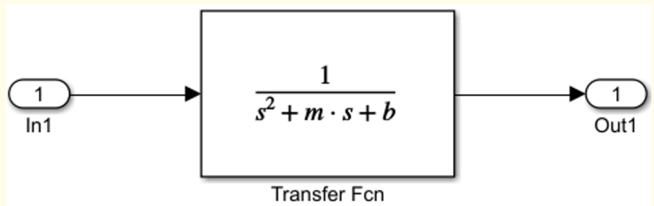

Figure 6B: Second Order NLMPC Transfer Function.

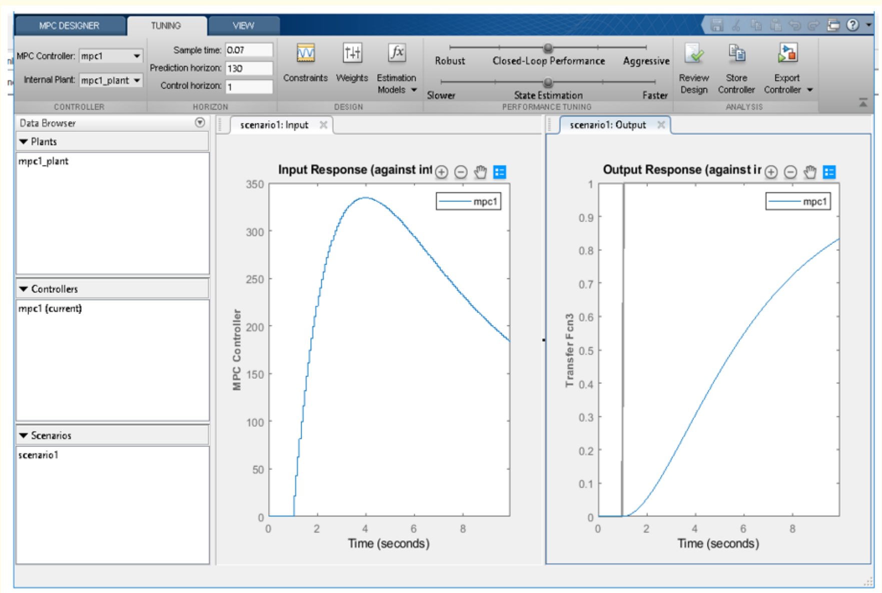

Figure 6C: Second Order NLMPC Plot.

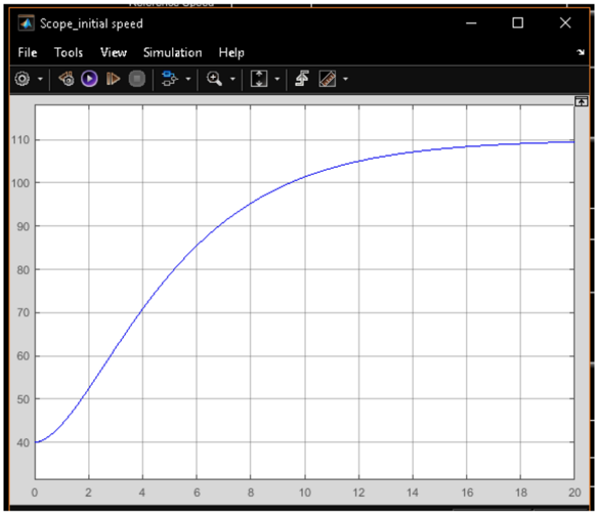

Figure 6D: Response of Initial Speed from Scope.

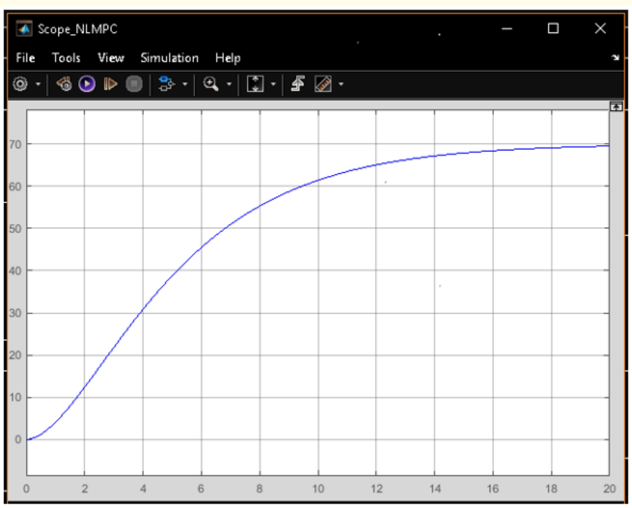

Figure 6E: Nonlinear MPC Response from Scope.

The idea of the NMPC scheme is as follows: at each sampling instant n we optimize the predicted future behavior of the system over a finite time horizon $k = 0, N-1$ of length $N \geq 2$ and use the first element of the resulting optimal control sequence as a feedback control value for the next sampling interval. In this section we give a detailed mathematical description of this basic idea for a constant reference $x_{ref} \equiv x_* \in X$. A prerequisite for being able to find a feedback law which stabilizes the system at x_* is that x_* is an equilibrium of the nominal closed-loop system, i.e., $x_* = f(x_*, \mu(x_*))$—this follows immediately with $g(x) = f(x, \mu(x))$. A necessary condition for this is that there exists a control value $u_* \in U$ with $x_* = f(x_*, u_*)$, which we will assume in the sequel. The cost function to be used in our optimization should penalize the distance of an arbitrary state $x \in X$ to x_*. In addition, it is often desired to penalize the control $u \in U$. This can be useful for computational reasons, because optimal control problems may be easier to solve if the control variable is penalized. On the other hand, penalizing u may also be desired for modeling purposes, e.g., because we want to avoid the use of control values $u \in U$ corresponding to expensive high energy. For these reasons, we choose our cost function to be of the form $l: X \times U \rightarrow$. In any case, we require that if we are in the equilibrium x_* and use the control value u_* in order to stay in the equilibrium, then the cost should be 0. Outside the equilibrium, however, the cost should be positive, i.e., $l(x_*, u_*) = 0$ and $l(x, u) > 0$ for all $x \in X$, $u \in U$ with $x \neq x_*$ [6].

Piecewise linear (PL) systems or more precisely, piecewise affine systems are an attractive class of nonlinear systems that have been used to represent a range of system nonlinearities in many applications such as saturation, relays and dead zones. By approximating a nonlinear system as a family of piecewise affine systems, the analysis of the nonlinear system is transformed into an analysis of several linear systems [7].

Over the last decade, a solid theoretical foundation for MPC has emerged so that for real-life large scale MIMO applications controllers with non-conservative stability guarantees can be designed routinely and with ease. The big drawback of MPC is the relatively formidable on-line computational effort which limits its applicability to relatively slow and/or small problems. Rather than solving the optimization problem online, recently, Bemporad., *et al.* proposed an approach where all computation is moved offline, for linear systems with a quadratic performance index, linear systems with a linear performance index, and hybrid systems with a linear performance index. The idea stems from observing that the linear part of the objective and the right-hand side of the constraints in the optimization problem depend linearly on the state vector x(t), which is treated as a vector of parameters. Then the optimization problem can be recast as a multiple parametric program and can be solved off-line by using the appropriate solver. The off-line solution is shown to be a piecewise linear function of the state and therefore the on-line computation reduces to a simple function evaluation. A fundamental question about MPC is its robustness with respect to model uncertainty and noise. When we say that a control system is robust we mean that stability is achieved and the performance specifications are met for a specified range of model variations and a class of noise signals (uncertainty range) [8].

Results

The following figures show the second-order cruise control system without any type of control. Figure 7A shows the second-order plant model without the control. Figure 7B shows the second-order plant model plant's block diagram components. Figure 7C shows the output plot of the second-order plant model without the control.

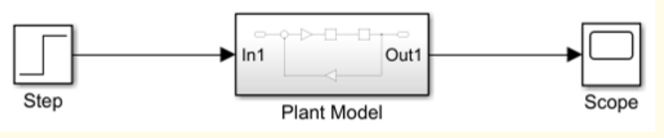

Figure 7A: Second-Order Plant Model without Control Block Diagram.

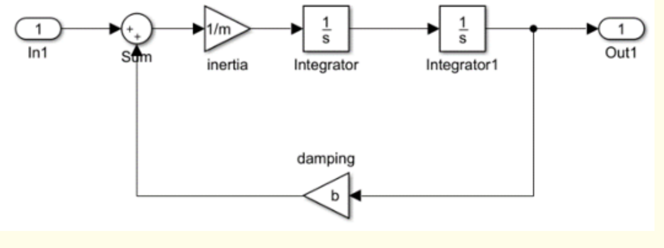

Figure 7B: Second-Order Plant Model Inside Plant.

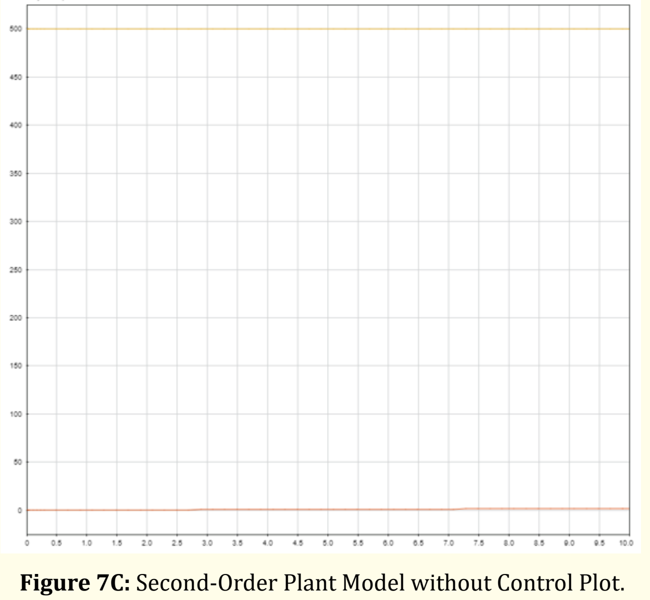

Figure 7C: Second-Order Plant Model without Control Plot.

In order to have a good representation of the Cruise Control using Linear Model Predictive Control, a simulation was use to represent the plant and the LMPC. Input response was used (Speed) and the output response of the model was represented using the scope, we can see the behavior on the system showing in the plot. It was modeled using 10 seconds.

As we know, the Nonlinear Model Predictive Control does not start from an initial speed of zero. We needed to create a constant speed every cycle to add it to the reference speed. The constant speed we chose was 40 MPH. The reference speed we set as 70 MPH. Tuning was needed for the NLMPC to observe a good response in addition to a zero steady-state error.

In order to tune the NLMPC, we needed to modify the parameters for the sample time, prediction horizon, and control horizon. The value for the sample time was set to 0.07 seconds. The value for the prediction horizon was set to 130. The value for the control horizon was set to 1.

Overall, we observed that the Linear Model Predictive Control and Nonlinear Model Predictive improved the conventional cruise control system of the PHEV compared to the baseline cruise control system's plant without control. LMPC provided a baseline of our MPC control for the cruise system, before implementing the NLMPC. Overall, speeds greater than 70 MPH is not recommended for conventional cruise controls systems using either the Linear Model Predictive Control (LMPC) or Nonlinear Model Predictive Control (NLMPC) stated in this paper. As speeds increases, so does the potential computation time the control system needs to compensate for road conditions and predictions. Thus, speeds greater than 70 MPH would be more suited to Adaptive Cruise Control (ACC) systems, which may be explored in future research based on some parameters of the Chrysler Pacifica Hybrid minivan.

Currently there about three types of cruise control systems. The three types of cruise controls systems are speed limiter, Adaptive Cruise Control (ACC), and semi-autonomous cruise control. A speed limiter system will limit how fast the driver can accelerate based on the vehicle's speed limiter which in turn is capped by the vehicle's manufacturer as a specified set point value. Adaptive Cruise Control (ACC) uses sensors such as cameras and radar-based (radio detection and ranging) systems and LiDAR-based (light detection and ranging) systems. This can also be used in conjunction with sensor fusion and possible Kalman filtering techniques. Semi-autonomous Cruise Control can be considered as Adaptive Cruise Control (ACC) in addition to driver assistance features, such as side blind zone monitoring, lane guidance, steering guidance, and an automated braking systems [9].

The Model Predictive Control (MPC) system that was discussed in this paper can be used as a cost-efficient method before entering the domains of Adaptive Cruise Control (ACC) and Semi-autonomous Cruise Control systems.

These advancements will be crucial for the higher levels of semi-autonomous and fully autonomous of electric vehicles as defined by SAE International's "SAE J3016 Recommended Practice: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles" specification. This specification is generally referenced as the SAE Levels of Driving Automation. Per SAE, "SAE J3016 defines the SAE Levels from Level 0 (no driving automation) to Level 5 (full driving automation) in the context of motor vehicles and their operation on roadways." [10].

The SAE levels of autonomous vehicles are summarizes in Table 1 as shown below [10,11].

SAE Levels of Autonomous Vehicles	
Level 0	No Automation
Level 1	Driver Assistance
Level 2	Partial Automation
Level 3	Conditional Automation
Level 4	High Automation
Level 5	Full Automation

Table 1: SAE Levels of Autonomous Vehicles.

Ultimately, the automotive industries' goals to have fully electric vehicles with self-driving capabilities and therefore removing the need for a steering wheel and therefore input from the driver from the vehicle.

Conclusion

In conclusion, Model Predictive Control (MPC) is an effective control method in implementing to control a PHEV's conventional cruise control system. Overall MPC contributes to improved control in either linear or nonlinear forms versus no controller. MPC is another type of controller that can be implemented in automotive applications in addition to the Proportional–Integral–Derivative (PID) controllers that are currently used in industry in automotive calibration. Besides switching from a conventional cruise control system to an adaptive cruise control (ACC) system, other factors such as aftermarket shocks, suspension/chassis components which in turn could lower rider height to achieve a lower center of gravity, performance tires, and potential weight reduction i.e., the removal of the spare tire and additional passenger seating row may help to provide better performance results. As lithium-ion batteries become more cost efficient to produce and also optimize the high-voltage (HV) battery pack's weight and cell configuration, could led to potential weight reductions, which in turn can lower not only the HV battery pack's weight, but also the total vehicle weight.

Future Work

As plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and mild hybrids become more complex, then more advanced control techniques will be needed. Future improvements to this simulation would be to use real-world data and also to expand the concept of linear Model Predictive Control (LMPC) and nonlinear Model Predictive Control (NLMPC) described in this paper to Adaptive Cruise Control (ACC). A Model Predictive Estimator is also being considered for both Conventional Cruise Control and Adaptive Cruise Control (ACC). Another expansion would be to consider Artificial Neural Networks (ANNs) and Machine Learning (ML) techniques can also be applied in addition to Model Predictive Control in order to further enhance an MPC-based conventional cruise control system as shown in [12]. This source is for commercial vehicles but can be adaptive for passenger vehicles.

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