

Cruise Controller with Fuel Optimization Based on Adaptive Nonlinear Predictive Control

Ondrej Santin, Jaroslav Pekar, and Jaroslav Beran
Honeywell Automotive Software

Anthony D'Amato, Engin Ozatay, John Michelini, Steven Szwabowski, and Dimitar Filev
Ford Motor Company

ABSTRACT

Automotive cruise control systems are used to automatically maintain the speed of a vehicle at a desired speed set-point. It has been shown that fuel economy while in cruise control can be improved using advanced control methods. The objective of this paper is to validate an Adaptive Nonlinear Model Predictive Controller (ANLMPC) implemented in a vehicle equipped with standard production Powertrain Control Module (PCM). Application and analysis of Model Predictive Control utilizing road grade preview information has been reported by many authors, namely for commercial vehicles. The authors reported simulations and application of linear and nonlinear MPC based on models with fixed parameters, which may lead to inaccurate results in the real world driving conditions. The significant noise factors are namely vehicle mass, actual weather conditions, fuel type, etc. In the ANLMPC approach, the vehicle and fuel model parameters are adapted automatically, so accuracy of the prediction is ensured. The adaptation is implemented by a Recursive Least Square (RLS) algorithm and the numerical robustness is improved by adopting Bierman's implementation with exponential/directional forgetting, and with suitable RLS stopping condition. The ANLMPC has been validated in real world driving conditions running in a production PCM module of a Sport Utility Vehicle (SUV), showing up to 2.4% fuel economy improvement in average compared to the production cruise controller with the same time of arrival. It has been confirmed that the ANLMPC can be run in a standard PCM module with single precision arithmetic, together with its other powertrain control functions.

CITATION: Santin, O., Pekar, J., Beran, J., D'Amato, A. et al., "Cruise Controller with Fuel Optimization Based on Adaptive Nonlinear Predictive Control," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 9(2):2016, doi:10.4271/2016-01-0155.

INTRODUCTION

Standard cruise control systems are designed so that the vehicle speed tracks the driver's desired setpoint by manipulating the engine torque employing the proportional feedback enhanced with integral action, see e.g. [1] and references therein for brief history development of cruise systems. In these systems, the vehicle speed is tracked despite significant grade and changing nominal conditions, such as wind, vehicle aging, etc. As a result, such strategies are not guaranteed to be fuel optimal, and maybe objectionable to the driver in terms of comfort.

On the other hand, the application of Model Predictive Control (MPC) for cruise in heavy duty applications has been studied in many works, see for example [2, 3 and 4] and references therein with indication of fuel economy benefit of this technology. Analysis of the application of MPC in place of standard cruise control for passenger cars with the goal of maximizing fuel economy in urban traffic is given in [5, 6, 7, and 8]. Alternative approaches to the problem of real time fuel economy optimization using road and traffic information are discussed in [9, 10, 11, and 12]. A common objective of these works is to optimize vehicle fuel economy by using additional information about future road grade, traffic conditions and by exploiting the relationship between the vehicle speed, torque and fuel

consumption (fuel map). It has been shown e.g. in [3, 6] that utilizing such information in combination with a real-time optimization algorithm results in improved fuel economy in comparison to the standard cruise control methodologies.

An advantage of using Adaptive Nonlinear Model Predictive Controller (ANLMPC) technology for cruise control applications is its ability to use information about the road grade ahead of the cruising vehicle. Such information is available, for example, from onboard 3D maps, or GPS systems. Proposed ANLMPC uses information about the road grade over the prediction horizon to optimize vehicle fuel economy while respecting specified constraints. The constraints can include, for example, vehicle speed range, average speed, distance to a lead vehicle, or transmission limitations. The resulting constrained optimization problem is solved online at each sample period using ANLMPC, resulting in a speed trajectory that is fuel optimal given the specified constraints.

In order to optimize fuel economy it is necessary to utilize additional degrees of freedom, in this work, by replacing the driver's desired speed setpoint with a driver selectable speed range. The vehicle speed range is an enabler for the optimization where the expected fuel benefits are

linked to the range size and nonlinearities in the vehicle and fuel models. A theoretical analysis of possible fuel benefits linked to the vehicle and fuel model under various control strategies is provided in [2].

The objective of this report is to summarize results achieved by applying ANLMPC to a predictive cruise control system in a production Lincoln MKT with the goal of optimizing fuel economy and taking into account limited resources of production Powertrain Control Module (PCM) unit. This paper is organized as follows: the second section introduces the plant description and modeling approach, including model adaptation; the third section provides the description of implemented nonlinear model predictive control algorithm; results obtained in real world driving conditions together with implementation details are provided in the fourth section.

CONTROL ORIENTED MODELING

A suitable model structure is required for ANLMPC control design. The model is used in real-time to predict the dynamic behavior of the vehicle over the prediction horizon followed by optimization of the speed trajectory. Therefore the vehicle model must be a Control Oriented Model suitable for real-time implementation. The vehicle model is composed of several subsystems. The key high level components from the control point of view are:

- *Longitudinal Vehicle Model* - important for the prediction and feedback control of the vehicle speed
- *Fuel Consumption Model* - important for fuel economy optimization
- *Lead Vehicle Model* - used to predict the behavior of the lead vehicle, if present, and distance between the host and lead vehicles. The minimum distance can be controlled by the proposed ANLMPC algorithm.
- *Real-Time Model Parameters Adaptation Algorithm* - account for various real world effects (e.g. head wind, different number of passengers, etc.)

Individual subsystems and system state observers are briefly discussed in the following sections.

Longitudinal Vehicle Model

A longitudinal movement of the vehicle can be described by the Newton's second law of motion as

$$m \frac{dv}{dt} = F_{Trac} - F_{Aero} - F_{Roll} - F_{Grade} - F_{Brake} \quad (1)$$

Where the forces are defined as:

$$\begin{aligned} F_{Trac} &= \frac{\xi_{DL}}{R_{WH}} \gamma(G) R_{FDR} T, \\ F_{Aero} &= \frac{1}{2} \rho C_d A v^2, \\ F_{Roll} &= mg(k_1 v^2 + k_2) \cos \phi, \\ F_{Grade} &= mg \sin \phi. \end{aligned}$$

All used symbols are defined at the end of paper in the section titled Definitions/Abbreviations. The traction force F_{Trac} is created by the torque T generated by the internal combustion engine connected via gear box with selected gear G to the wheels with radius R_{WH} . The force F_{Aero} represents quadratic increase of resistance with vehicle speed due to the aerodynamic drag, while terms F_{Roll} and F_{Grade} indicate split of the gravitation force depending on the road grade ϕ together with rolling resistance.

The model (1) is based on the vehicle dynamics. However, the values of parameters listed above can fluctuate in real world driving conditions, e.g. vehicle mass is changed with number of passengers or vehicle load, ambient conditions, different quality of tires, wind, etc. It is known that model quality is important for the final performance of any MPC controller and therefore a simplified model with parameter adaptation has been introduced.

The structure of model can be simplified using the small angle approximation with reduced number of parameters as

$$\frac{dv(T, v, \phi)}{dt} = \beta_1 T + \beta_2 v^2 + \beta_3 \phi + \beta_4 \quad (2)$$

The assumption is that the road grade is relatively small and therefore $\sin \phi$ function may be approximated well by ϕ . As a result, model (2) consists of the main relations such as: acceleration created via generated torque, aerodynamic drag and rolling resistance as function of road grade while reducing the number of parameters. Comparison of the measured data and vehicle acceleration for model (1) and simplified model (2) is depicted in Figure 1. This demonstrated that the simplified model captures real acceleration in a similar fashion as more complicated model with more parameters. Moreover, when the parameters of model (2) are adapted, even better fit can be achieved as depicted. For this test, the vehicle has been in cruise at 55 mph running the ANLMPC controller on a Southeast Michigan highway express road. Note that the main nonlinearity of the simplified model (2) is the aerodynamic resistance.

Next, the model (2) is augmented with a disturbance term d_v as it is shown in following equation

$$\frac{dv(T, v, \phi, d_v)}{dt} = \beta_1 T + \beta_2 v^2 + \beta_3 \phi + \beta_4 + d_v \quad (3)$$

where d_v is used to achieve offset-free tracking in the ANLMPC controller. See [13] for more details about how to introduce the integral action in MPC control. While performing a similar function to β_4 , which is online adapted slowly with time (see next section), d_v is estimated using an Extended Kalman filter at a quicker rate than the β_i model parameters. The parameter d_v can be used in a diagnostic to monitor the model quality. If the model accuracy is high then the disturbance term $d_v \rightarrow 0$.

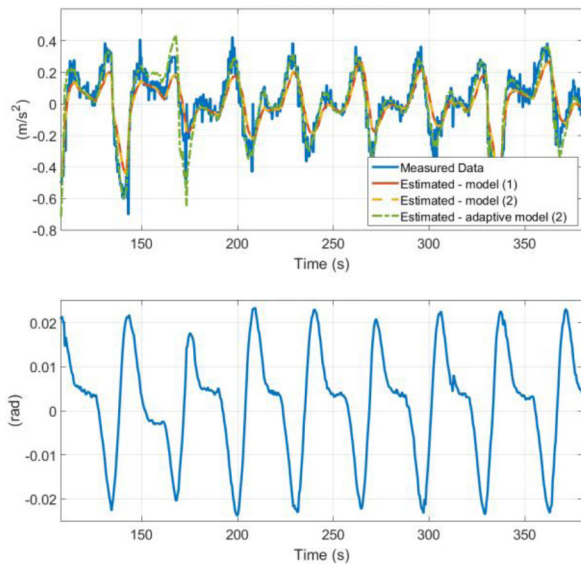


Figure 1. Comparison of full nonlinear (1) and simplified model (2) estimated acceleration to measured vehicle acceleration on Test Route 1

Fuel Consumption Model

A fuel flow rate model is required in this application since the objective of the ANLMPC algorithm is fuel economy optimization. The second order polynomial model in torque with bilinear term of vehicle speed and engine torque defined as

$$\dot{m}_{Fuel}(T, v) = c_4 T^2 + c_3 T + c_2 T v + c_1 v + c_0, \quad (4)$$

was shown to provide acceptable accuracy for this application. The quality of the identified model based on data collected from the sport utility vehicle is illustrated in Figure 2, where the model output is compared with data measured on vehicle. The approximation (4) including the linear and bilinear term in vehicle speed gives reasonable accuracy.

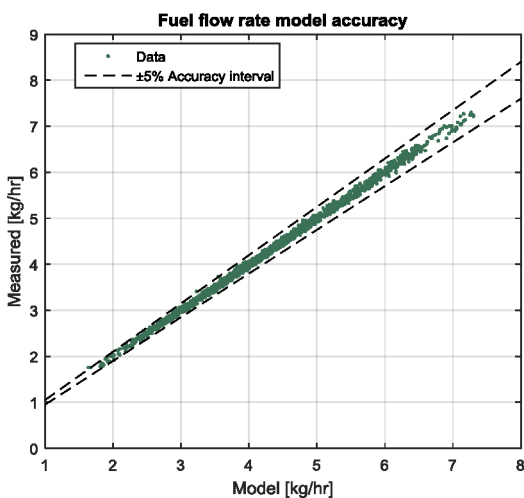


Figure 2. Accuracy of the fuel flow rate model

Model Parameter Adaptation

The controller plans optimal future trajectory of torque and vehicle speed based on the model. The vehicle parameters are subject to change in the real-world conditions (e.g. change of mass due different number of passengers, vehicle aging, head wind, rain, varying fuel quality etc.). Hence the model parameters have to change as well to capture the reality and produce reliable fit of vehicle behavior.

Our experiments suggest that when vehicle is in cruise the excitation of the system is low due limited range of torque and vehicle speed. As a result the persistent excitation is not present and application of standard exponential forgetting in Recursive Least Square (RLS) algorithm might lead to covariance growth and numerical issues. To prevent this, directional forgetting of [14] has been combined with square root algorithm [15]. The proposed algorithm which assures numerical robustness and prevents covariance wind-up without persistent excitation is described in Appendix.

The resulting RLS algorithm has been used for online adaptation of parameters β_i , $i = \{1, \dots, 4\}$ of the simplified model (2) and parameters c_i , $i = \{0, \dots, 5\}$ of the fuel rate model (4). The adaptation is running at the same sampling rate as controller. The adaptation of parameters of vehicle model (2) depends on the fitting to the estimated vehicle speed derivative based on finite difference. The estimation of fuel flow is used to fit parameters of fuel rate model (4). The initial values of β_i are derived by comparing the equations (2) and (1), while initial values of parameters c_i are result of linear mean square regression from measured data.

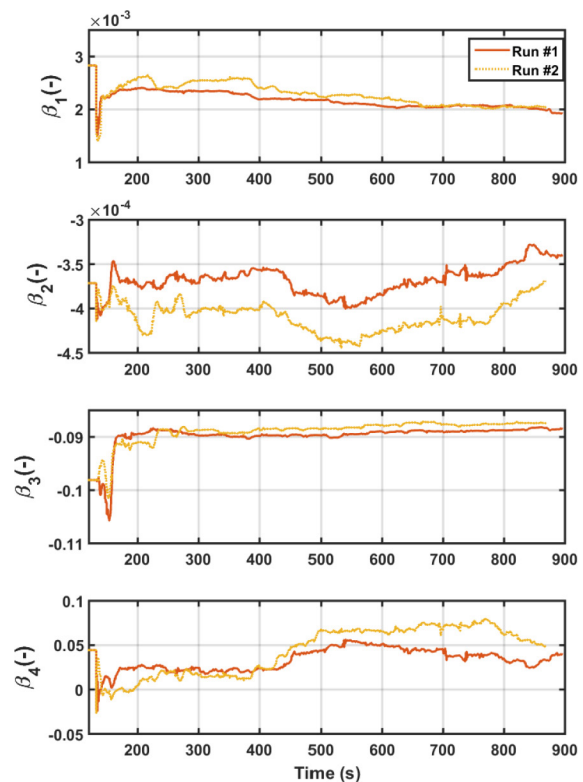


Figure 3. Vehicle model parameters comparison for two successive tests on Test Road #1

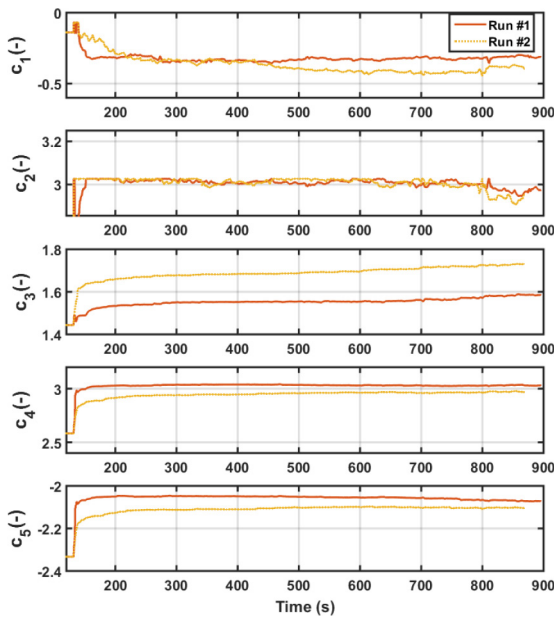


Figure 4. Fuel rate model parameters comparison for two successive tests on Test Road #1

In Figure 3 and Figure 4 the good repeatability of the model parameters for the two successive tests on the same road is depicted. Both models (2) and (4) have been adapted at a sample rate of 0.5s when vehicle was in cruise at 55mph running the ANLMPC controller on Test Road 1. Forgetting factor λ for the vehicle model was selected as 0.9995 representing about 17 minutes time window, while for fuel rate model 0.999 representing about 8 minutes of past measurements. At the beginning of each test the same initial parameters were used and covariance of the parameters has been reset to the same values.

Lead Vehicle Model

For vehicle safety, the ANLMPC algorithm should maintain a minimum prescribed distance to the lead vehicle. The lead vehicle model accuracy is limited in applications without Vehicle to Vehicle (V2V) systems, and even in this case cannot capture driver intent. Therefore, the lead vehicle is simplified. In this work, the lead vehicle is approximated by a second order system that can be described by

$$\frac{dv_2}{dt} = a_2; \quad \frac{da_2}{dt} = -\frac{1}{\tau_2} a_2 \quad (5)$$

Where v_2 is actual speed of the lead vehicle, a_2 is acceleration and τ_2 is a time constant representing expected time of acceleration. The dynamics of the lead vehicle are such that the acceleration is assumed to decay to zero over the prediction horizon with time constant τ_2 . The lead vehicle model is used by the ANLMPC controller to ensure minimum gap between the host and lead vehicles. The relative distance D_2 between the vehicles can be described by a first order differential equation

$$\frac{dD_2}{dt} = v_2 - v \quad (6)$$

Note that the distance to the lead vehicle can be measured by an onboard forward facing radar and therefore it is possible to estimate actual speed and acceleration of the lead vehicle. To eliminate measurement error and noise, a linear Kalman filter (KF) is used. The model for the KF is (5) and (6) where the distance D_2 is measured by the radar. The distance provided by the radar is reliable only in a certain range, and therefore it is necessary to ensure correct initialization and detection of the lead vehicle on the horizon. It should be noted that in the absence of forward facing radar or V2X systems, ANLMPC can still be used to optimize fuel economy in cruise control, with the exception that distance to the lead vehicle constraint violations will require human intervention.

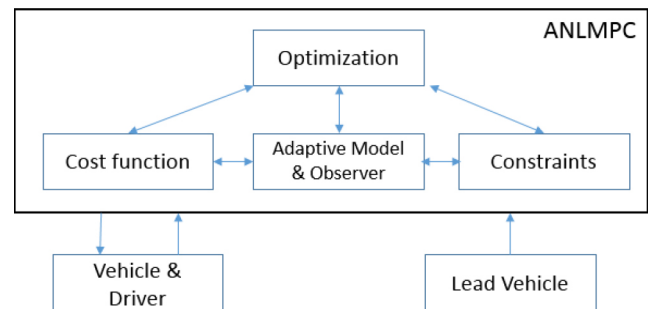


Figure 5. A high level structure of the ANLMPC controller

NONLINEAR MPC FOR CRUISE CONTROL APPLICATIONS

The ANLMPC is able to outperform a standard cruise control by utilizing known future trajectories of disturbance variables, for example, road grade ahead of the host vehicle, or information about the lead vehicle. The objective for the controller is to optimize fuel economy while maintaining constraints. A high level structure of the ANLMPC algorithm is shown in Figure 5, where the main components of the algorithm are:

- **Optimization** - a core optimization routine of the ANLMPC algorithm. The ANLMPC is formulated as a Nonlinear Mathematical Programming (NLP) problem which can be efficiently solved on a real-time embedded platform (e.g. PCM).
- **Cost Function** - an objective function of the ANLMPC controller that is used to formulate the goals for the controller. The importance of individual goals is weighted by a set of factors (or calibration parameters) provided by the user.
- **Constraints** - a set of prescribed limits which must be satisfied by the controller. The limits are time varying and can be modified by the user in the real-time.
- **Adaptive Model and Observer** - a vehicle model is needed by ANLMPC controller to predict the future behavior based on which the optimal control action can be computed. The Extended Kalman Filter is used to filter and estimate host vehicle and lead vehicle states. The RL algorithm is used for model parameters adaptation.