

Launch Performance Optimization of GTDI-DCT Powertrain

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ABSTRACT

A direct trajectory optimization approach is developed to assess the capability of a GTDI-DCT Powertrain, with a Gasoline Turbocharged Direct Injection (GTDI) engine and Dual Clutch Transmission (DCT), to satisfy stringent drivability requirements during launch. The optimization is performed directly on a high fidelity black box powertrain model for which a single simulation of a launch event takes about 8 minutes. To address this challenging problem, an efficient parameterization of the control trajectory using Gaussian kernel functions and a Mesh Adaptive Direct Search optimizer are exploited. The results and observations are reported for the case of clutch torque optimization for launch at normal conditions, at high altitude conditions and at non-zero grade conditions. The results and observations are also presented for the case of simultaneous optimization of multiple actuator trajectories at normal conditions.

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INTRODUCTION

Trajectory optimization (optimal control) techniques can be exploited to assess achievable performance and feasibility for a given powertrain to meet specified targets, define and cascade targets from system level to subsystem level, drive hardware design modifications, assess calibration and control algorithm improvement opportunities, and develop calibration guidelines. They can also reveal novel actuator coordination patterns and system operation strategies. See [9, 10, 11] for specific examples.

Optimal control of transmission clutch engagement during launch has received much attention in the literature, see [3, 4, 5, 6, 7, 14], as it is critical for drivability of vehicles with automated manual and dual clutch transmission. Related problems of robust optimal H_∞ and μ control have also been studied, see e.g. [13] and references therein. For turbocharged engines with dual clutch transmissions, intricate trade-offs between early clutch engagement to provide responsiveness and more gradual engagement to bring engine speed and boost pressure higher for faster overall acceleration have been exemplified in [4]. The introduction of dry clutch transmissions in combination with turbocharged gasoline direct injection engines into worldwide markets has recently taken place, and further measures for drivability optimization of these powertrains, especially for the North American customers, are of significant interest.

In this paper, we pursue trajectory optimization of a launch event for a powertrain with a gasoline direct injection engine and a dual clutch transmission. Compared to existing literature, our approach is distinguished by the optimization of trajectories of both the clutch and engine actuators (spark timing and valve timing while throttle is wide open) on high fidelity powertrain models with engine model in GT-Power¹ co-simulated with the transmission model in VDM². Performing optimization directly on the high fidelity model is desirable as, unlike simpler control oriented models, the high fidelity model is predictive, e.g., it can reflect the effect of hardware parameter changes, and it can also represent detailed behavior of the powertrain in response to not only the clutch but also engine actuators. This high fidelity model has also been validated against vehicle data and is trusted by development engineers who use it routinely for powertrain development. The development and identification of a simpler model to match data of the high fidelity is in principle also possible. However, the model simplification step would require time and effort every time hardware parameters need to be changed in the high fidelity model, and it is not straightforward to automate. The main challenge integrating the high fidelity model into the optimization is that it runs slowly. This model is also largely black-box; writing down the equations analytically or even precisely determining the number of dynamic states is impossible. Such a situation is not atypical of trajectory optimization problems in

1. GT-Power is a registered trademark of Gamma Technologies, <http://www.gtisoftware.com/>.
2. VDM is Ford Motor Company proprietary transmission modeling tool.

industrial applications, where it is desirable to perform optimization directly on high complexity integrated system level models. In addition to treating this high complexity black box model, in this paper we consider a more comprehensive set of drivability constraints than those treated in the prior literature, that are derived from customer requirements. Furthermore, in addition to treating the launch at normal conditions, we also consider launch at high altitude conditions and launch on a non-zero grade.

In our previous work [8], we have proposed an iterative model and trajectory refinement (IMTR) strategy for dealing with high complexity trajectory optimization problems. The IMTR exploits an adjustable low fidelity model and uses intertwined steps of trajectory optimization on a low fidelity model and mismatch estimation to adjust the low fidelity model to approximate the high fidelity model. For clutch trajectory optimization, we were able to prescribe the low fidelity model based on engine and vehicle speeds as the only two states. The IMTR approach has been overall successful for clutch trajectory optimization, provided the initial clutch torque trajectory was sufficiently close to the optimal one. However, extending IMTR approach to simultaneous optimization of engine actuators and the clutch has proven to be more complicated as developing a suitable low fidelity model for the dynamic effect of the engine actuators on the engine torque requires a substantial effort. Consequently, in this paper we pursue a direct optimization approach on the high fidelity model, while exploiting the efficient input parameterization and Mesh Adaptive Direct Search (MADS) techniques [2].

The paper is organized as follows. We first provide further description of the powertrain model that we exploit in this work. We then describe the details of the problem formulation and drivability constraints. The trajectory optimization methodology is summarized along with the process of applying it to our optimization problem. Finally, the results and concluding remarks are presented.

POWERTRAIN MODELING

The trajectory optimization is performed on a high fidelity model representing a powertrain with Ford EcoBoost Gasoline Turbocharged Direct Injection (GTDI) engine and Getrag 6DCT250 six-speed, dual dry clutch transmission. See Figure 1 for the schematics of the powertrain. The engine model is implemented in GT-Power. The transmission model is implemented in a Ford proprietary modeling environment VDM. The transmission model in the form of an S-function is integrated with the co-simulated engine model in Simulink. Basic engine and transmission controller models are also integrated into the simulation.

The high fidelity model provides accurate representation of the powertrain dynamics suitable for realistic prediction of powertrain operation including the effect of design changes. Unfortunately, this model also has high complexity with over 100 discrete and continuous states. A single launch event simulation takes about 8 min on a desktop computer with 2.2GHz clock speed. As compared to [8], the model used in this work has higher complexity as it has a more detailed, crank angle based engine dynamics model in GT-Power

(rather than a mean-value model in Simulink in [8]), and is 40 times slower. Thus the objective function and constraints based on this model simulations are expensive to evaluate.

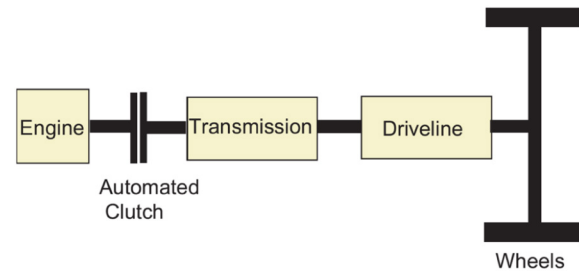


Figure 1. Powertrain schematics

To provide conceptual understanding of the actuators' effects on the vehicle acceleration, the following low-fidelity model is introduced. The engine speed dynamics prior to the clutch lock-up has the form,

$$\dot{\omega}_e = \frac{1}{J_e}(T_e - \beta_e \omega_e - T_{cl}), \quad (1)$$

and the vehicle speed dynamics has the form,

$$\dot{v}_v = \begin{cases} \frac{1}{J_v}(T_{cl} - \beta_v v_v - T_L) & \text{before lock-up,} \\ \frac{1}{J'_v}(T_e - \beta_v v_v - T_L) & \text{after lock-up,} \end{cases} \quad (2)$$

where ω_e is the rotational speed of the engine, J_e is the engine inertia, J_v is the effective vehicle inertia before the clutch lock-up, J'_v is the effective vehicle inertia after the clutch lock-up, T_e is the engine torque, T_{cl} is the clutch torque, T_L is the load torque from the vehicle reflecting aerodynamic drag and rolling resistance losses, and v_v is the vehicle speed, which, assuming zero slip, is proportional to wheel speed, ω_w (the proportionality constant is absorbed into J_v and J'_v). Since the launch occurs in the first gear and the gear ratio is known, the transmission input shaft speed, ω_p , is proportional to wheel speed, ω_w , and, assuming zero slip, to the vehicle speed, v_v . Note that after the clutch lock-up, engine speed and input shaft speed are synchronized. The clutch torque determines the vehicle acceleration before the lock-up; after the lock-up, the engine torque determines the vehicle acceleration.

PROBLEM FORMULATION

Drivability requirements during wide open throttle launch are summarized in Table 1, where $\ddot{v}_v$ is the normalized vehicle acceleration and t is the normalized time. Table 1 lists the constraints. The constraints include a constraint on the average acceleration during the launch period (C_3) which directly relates to terminal vehicle speed. They also include the pointwise-in-time constraints on the initial vehicle acceleration (C_1 and C_2) to ensure the vehicle is responsive, and a constraint on the clutch energy to protect the clutch and extend its durability. A soft landing constraint is also introduced to reduce discontinuous change in vehicle acceleration and shuffle

mode excitation at synchronization. Constants c_1 , c_2 , c_3 , c_{CE} and c_{SL} represent the constraint targets; acceptable launch events would meet every target criterion in Table 1.

Since the constrained problem has no objective function, we choose C_3 (average acceleration or, equivalently, terminal velocity) as an optimization objective, and we maximize it subject to other constraints. Throughout the rest of the paper, constraints refer to the constraints in Table 1 other than C_3 while by cost function we refer to C_3 .

Table 1. Constraints

Name	Description	Target
C_1	Time after launch to $\dot{v}_v = 0.01$	$< c_1$
C_2	Acceleration at 0.33 t -unit after launch	$\geq c_2$
C_3	Average acceleration during launch	$\geq c_3$
Clutch Energy	$E = \int_0^{t_s} [\omega_e(t) - \omega_i(t)] T_{cl}(t) dt$	$< c_{CE}$
Soft Landing	Input shaft acceleration, $\dot{\omega}_i$, matches engine acceleration, $\dot{\omega}_e$, at synchronization	$ \dot{\omega}_e(t_s) - \dot{\omega}_i(t_s) < c_{SL}$

Trajectory Optimization Methodology

Trajectory optimization problems can be solved using indirect or direct approaches.

In indirect approaches, necessary conditions of Pontryagin's Maximum Principle (PMP) are exploited leading to a two point boundary value problem which is solved using shooting or collocation type techniques. Indirect methods exhibit fast convergence locally (i.e., when already close to the solution), however, require additional procedures, such as homotopy, to obtain convergence when a good initial guess for the trajectory is unavailable.

The main impediment to applying indirect techniques to our problem is that the closed-form analytical expressions for model equations are unavailable, in fact, even the number of states in our black box model is unknown. For that reason and also due to high dimensionality of the state vector, dynamic programming approaches are also ruled out.

The direct methods can still be used. If the model is represented by

$$\dot{x} = f(x, u), \quad (3)$$

where u is an m -vector, direct methods proceed by parameterizing each input, e.g., as

$$u_i(t) = \sum_{j=1}^N k_{ij} \phi_j(t - t_j), \quad i = 1, \dots, m, \quad (4)$$

where $\phi_j(\cdot)$ are given basis functions and k_{ij} are coefficients that are determined through numerical optimization. The process of parameterizing the inputs is called transcription, and as a result of this transcription the problem is reduced to the conventional constrained

optimization problem. The direct methods are applicable to black box models as long as the evaluation of the objective function and constraints is feasible through simulations.

Given that each function evaluation is expensive, efficient parameterization of the inputs in Eq. (4) and efficient optimizers are required.

Gaussian Kernel Transcription

We use sums of Gaussian kernel functions to represent the inputs $u_i(t)$ in Eq. (4):

$$u_i(t) = \sum_{j=1}^N \frac{k_{ij} e^{-\frac{(t - \frac{(j-1)}{N} T)^2}{2\sigma^2}}}{\sum_{j=1}^N e^{-\frac{(t - \frac{(j-1)}{N} T)^2}{2\sigma^2}}}, \quad (5)$$

with σ defined as

$$\sigma = \frac{T}{3(N-1)},$$

where $i = 1, \dots, m$, k_{ij} are the parameters to be optimized, T is the time horizon (final time) of the optimization problem and N is the number of Gaussian kernels.

The functions of Eq. (5) are convenient and efficient in approximating time domain inputs. Figure 2 illustrates an approximation of a function with Gaussian kernels. In this example, $N = 5$ Gaussian kernels are used to generate a trajectory that closely approximates the target trajectory with $T = 5$ final time. We note that Gaussian kernel functions are smooth and hence the trajectory they represent, Eq. (5), is also smooth. This is important in models where discontinuous input jumps can cause numerical integration issues. We also note that more accurate transcription can be achieved by using more kernels yet more parameters mean higher complexity in optimization and can slow down the optimization process.

We use two strategies in the application of Gaussian kernel transcription to our powertrain launch trajectory optimization problem. We parameterize the trajectory of the clutch torque input, and for engine actuators (spark timing, exhaust valve closing (EVC) timing, intake valve opening timing (IVO)) we parameterize the additive perturbation (offset) to the nominal engine actuator output determined by the existing control strategy. Thus u_1 is the clutch torque and u_2, u_3, u_4 are additive perturbation inputs modifying spark timing, EVC, and IVO generated by the nominal control strategy. This approach is adopted as we can impose zero initial guesses for the additive perturbation inputs, and it is easier to guarantee that the additive perturbation inputs are within feasible ranges by constraining the perturbation size rather than the actual input size.

Denoting the vector of parameters k_{ij} that are being optimized in the input parameterization of Eq. (5) by X , the finite dimensional nonlinear programming problem that we need to solve has the following