Adjoint-based system identification and feedforward control optimization in automotive powertrain subsystems

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Abstract

Tuning the response of automotive powertrain subsystems can both improve performance and ease overall system integration in both conventional powertrains and innovative new powertrain designs. Existing control strategies for both the powertrain and its subsystems usually incorporate extensive feedforward maps (a.k.a. "look-up tables") because the systems of interest are nonlinear and difficult to model, operating ranges of interest are large, and maps are relatively inexpensive to implement. Augmenting or replacing such maps with dynamic feedforward control strategies based on predictive dynamic models can possibly provide significant performance improvements. The present work develops adjoint-based optimization approaches to

1) identify the several unknown parameters of a nonlinear model of a powertrain torque converter and transmission using empirical data, and

2) based on this identified model, optimize the feedforward controls for a powertrain gear shift to achieve the desired shift characteristics.

It is shown that the adjoint-based system identification procedure yields an accurate system model and that the adjoint-based control optimization procedure improves the anticipated system performance.

Nomenclature

θ_i	model parameters ($i = 1,2,3,\dots$)	t	time
		T	terminal time
Υ	torque	N	angular speed
$\mathbf{q}$	system states	$\mathbf{r}$	adjoint states
ϕ	control inputs	ψ	disturbance inputs
$\mathbf{y}$	measurements	$\mathbf{s}$	setpoints
η	efficiency	$()^*$	transpose
$()_f$	engine flywheel	$()_o$	initial condition
$()_p$	propeller shaft	$()_t$	turbine

1 Introduction

Control algorithms for mass produced automobiles must be computationally inexpensive, robust to parameter variations, simple to implement, and convenient to calibrate. Automobile powertrains must function over large operating ranges, and their accurate mathematical representation often requires complex nonlinear models. Hence, the standard approach to automotive subsystem control almost always incorporates a feedforward or open-loop strategy implemented as a set of maps based on experimental data and engineering judgment.

The interest in more accurately-tuned techniques for the control of powertrain subsystems increases with the number of advanced technology powertrain variants being considered for mass production, as well-controlled subsystems make total system integration more tractable and cost effective. Potential improvements on traditional methods for powertrain control are discussed in, e.g., [10], [8], and [1]. Most such developments require the prediction of the system behavior using dynamic mathematical models with parameters that must be identified experimentally. These models are used to develop the feedforward control strategies and rely heavily on experimental data for both system identification and verification of the control effectiveness. The present work develops and implements adjoint-based optimization procedures such that both the parameter selection and the tuning of the control inputs may be conducted with an automated procedure. It is demonstrated that this approach can be applied successfully to identify the parameters of the phenomenological model and to design appropriate feedforward controls for a conventional powertrain.

In §2, we review the equations of motion for the torque converter subsystem based on a lumped-parameter fluid-mechanical model. We show that the first-order dynamic model introduced by [15] can be obtained in this manner. In §3, we describe the adjoint-based system identification algorithm used to determine the appropriate parameters of this model and present numerical results which demonstrate its effectiveness. The algorithm used is an extension of the adjoint-based optimization algorithm used in a variety of model predictive control (MPC) applications, including the application to turbulence control discussed in [2]. In §4, we discuss performance objectives that may be used in the formulation of the control optimization problem to insure physically relevant controls result. We then compare inputs and outputs of the original system (as represented by the data used in the system identification) to the inputs and outputs of the identified system model when the controls are optimized to achieve the stated objectives using an adjoint-based algorithm. The results demonstrate the flexibility of the approaches proposed for offline feedforward control design. Concluding remarks are presented in §5.

2 System model

The torque converter without a lock-up clutch is a passive fluid coupling device that rendered automobiles automatic as early as 1940, as discussed in detail in [4]. It provides a level of "driveability" that is difficult to surpass, but at the expense of system efficiency. Technical details about its mechanical design and utility can be found in [13]. Models that describe the static torque and speed relationships for the torque converter are available in [9] and [5]. The transient relationships of the characteristic parameters are shown by [15] to satisfy a first-order ODE model. In all of these modeling studies, the model parameters cannot be derived easily from the physical properties of the mechanical device and must therefore be fitted using empirical data. The utility of modeling this passive device is to predict disturbances that transfer between the engine brake torque and the transmission gear ratio associated with the vehicle load. Accurate predictions of the torque converter's transient response during a shift will facilitate powertrain design with improved engine load disturbance rejection and improved transmission input torque disturbance rejection.

Following [3], we may use a lumped parameter description to develop the equations of motion for the turbomachine given by the torque converter without a lock-up clutch, as shown in Figure 1. The impeller is bolted to the engine flywheel, and the turbine is the direct input to the transmission. The fluid control volumes adjacent to the impeller (to be called the impeller CV) and the turbine (to be called the turbine CV) share a common boundary, across which both angular momentum and automatic transmission fluid is transferred. Applying conservation of angular momentum to each of these fluid control volumes leads to:

$$\frac{\partial}{\partial t}\int_{CV} r\times\overrightarrow{V}\rho\, dV = -\int_{CS} r\times\overrightarrow{V}\rho\overrightarrow{V}\cdot d\overrightarrow{A} + r\times F_s + T_{shaft}. \tag{1}$$

The fluid density ρ is assumed to be constant, $\overrightarrow{V}(r)$ is the "lumped parameter" model of the fluid velocity in each control volume, CS is the control surface around the control volume CV, and r is the distance from the centerline. The left-hand side of (1) is the time rate of change of the total angular momentum of the fluid in the control volume. The right-hand side is the sum of three terms: 1) the convective transfer of angular momentum caused by fluid passing from one control volume to the other, 2) a "lumped parameter" model of the torque caused by fluid shear between the two volumes of fluid moving at different speeds, and 3) the torque acting on the fluid volume by either the turbine (for the turbine CV) or the impeller (for the impeller CV). Note that the fluid speed in the impeller CV is modeled as being proportional to the engine flywheel speed N_f and the fluid speed in the turbine CV is modeled as being proportional to the transmission input speed N_t. The shear force between these two volumes is modeled as a linear function of the slip between them, $F_s \propto N_f - N_t$. The externally applied mechanical torque T_{shaft} at the impeller is just the engine brake torque Υ_f measured at the flywheel, and the exter-

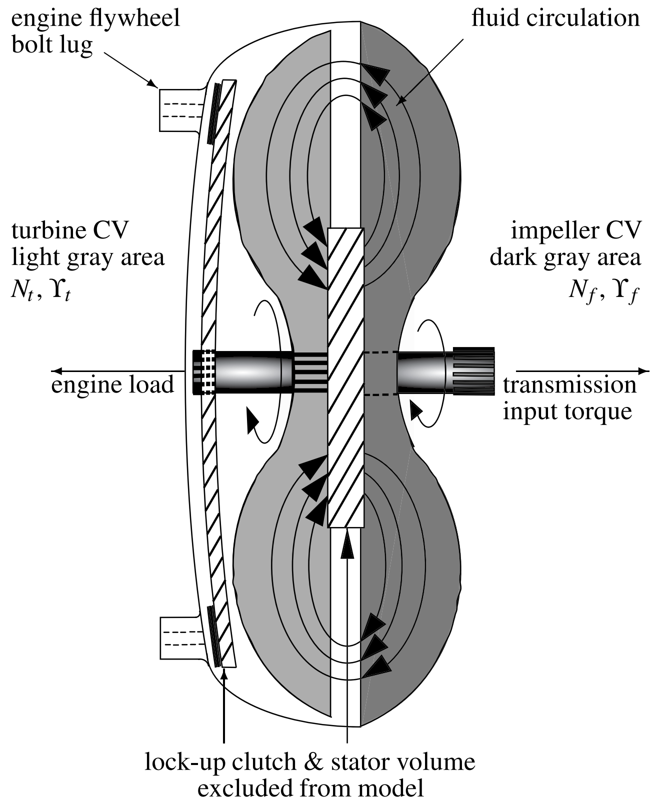

Figure 1: Cross-section schematic of a torque converter

nally applied mechanical torque T_{shaft} at the turbine is the so-called turbine torque Υ_t, which is the vehicle load torque transferred by the transmission.

For the purpose of system identification, the system output is chosen to be the full state consisting of both engine and turbine speed. Usually, the system inputs are the engine and turbine torque. However, the turbine torque measurement is not available. For the purpose of a single 1-2 upshift, preliminary investigations show that this signal can be sufficiently approximated by the expression[1]

$$\Upsilon_t \approx c_1 N_p + c_2\Upsilon_p + c_3\frac{N_f}{N_t}\Upsilon_f, \tag{2}$$

where the transmission propeller shaft torque, Υ_p, and speed, N_p, are accessible measurements. Now, the propeller shaft torque is essentially a control input along with the engine torque. The propeller shaft speed is a source of uncertain road load disturbances for the torque converter subsystem. Combining (1), for both the impeller and the turbine halves of the torque converter, with (2) and consolidating terms leads to the nonlinear equation governing the system:

$$\begin{aligned}\begin{pmatrix}\dot N_f\\ \dot N_t\end{pmatrix} = &\begin{pmatrix}\theta_1+\theta_3 N_f+\theta_4 N_t & \theta_2+\theta_5 N_t\\ \theta_{10}+\theta_{12}N_f+\theta_{13}N_t & \theta_{11}+\theta_{14}N_t\end{pmatrix}\begin{pmatrix}N_f\\ N_t\end{pmatrix} + \\ &\begin{pmatrix}\theta_6 & \theta_7 & \theta_8\frac{N_f}{N_t}+\theta_9\\ \theta_{15} & \theta_{16} & \theta_{17}\frac{N_f}{N_t}+\theta_{18}\end{pmatrix}\begin{pmatrix}N_p\\ \Upsilon_p\\ \Upsilon_f\end{pmatrix}.\end{aligned} \tag{3}$$

[1] Preliminary investigations also show that the approximation for this turbine torque signal for a 2-3 upshift may be different in structure; that is, its dependence on the inputs and states may be different from (2).

We see that the nonlinearities in this first-order system of equations are quadratic, in agreement with [15].

Models that describe the step-geared automatic transmission are widely available in the literature, from [6], [14], [17], [16], [12], [11], [7] and the references contained therein. When the transmission input is the actuating hydraulic pressure of each gear shifting device, or its directly proportional torque, the transmission output torque dynamics can be represented as a linear system response, as characterized in [17]. The disengaging gearing device produces a first order torque decrease response to the decreasing hydraulic pressure as fluid drains to deactivate the device. The engaging gearing device produces a 2nd order torque increase response to increasing hydraulic pressure that activates the device. The engine torque input can be a significant disturbance to the transmission output torque during a gear shift operation. The transmission output speed dynamics is modelled as the sum of the driving torque and the vehicle load which is assumed to be a linear function of the speed during a gear shift. The governing equations for the transmission output torque and speed, as measured at the propeller shaft, can be combined as follows.

$$\begin{pmatrix}\dot{N}_p\\ \dot{\Upsilon}_{p1}\\ \dot{\Upsilon}_{p2}\\ \dot{\Upsilon}_p\end{pmatrix}=\begin{pmatrix}\theta_{19}&0&0&\theta_{20}\\ 0&\theta_{21}&\theta_{22}&\theta_{23}\\ 0&\theta_{26}&\theta_{27}&\theta_{28}\\ 0&\theta_{31}&\theta_{32}&\theta_{33}\end{pmatrix}\begin{pmatrix}N_p\\ \Upsilon_{p1}\\ \Upsilon_{p2}\\ \Upsilon_p\end{pmatrix}+\begin{pmatrix}0&0&0\\ \theta_{24}&\theta_{25}&\theta_{36}\\ \theta_{29}&\theta_{30}&\theta_{37}\\ \theta_{34}&\theta_{35}&\theta_{38}\end{pmatrix}\begin{pmatrix}\Upsilon_f\\ \Upsilon_{c0}\\ \Upsilon_{c1}\end{pmatrix} \tag{4}$$

The torque inputs proportional to the hydraulic pressures that actuate the disengaging and engaging gear shifting devices are Υ_{c0} and Υ_{c1}, respectively. The internal states for the transmission output torque, Υ_p are designated Υ_{p1} and Υ_{p2}. Next, we develop the adjoint-based optimization model predictive system identification technique. The state space realization for the full torque converter and transmission combined system is defined in terms of the notation used to formulate the general parameter identification scheme.

3 Adjoint-based system identification

Adjoint analysis is a mathematical tool for determining the gradient information central to efficient high-dimensional optimization strategies. The principal modeling application for adjoint analysis in the present section is *model parameter identification.* That is, iterative simulations may be used to find the optimal values of the unknown parameters, $\theta=\{\theta_{1-38}\}$, such that the output of the proposed model in (3) & (4) fits the measured data. In the following section, we may then use this validated model to develop the control algorithm. The adjoint analysis used in this approach may be referred to as a sort of *open-loop optimization*. That is, iterative computer simulations may be used to optimize the schedule of torque converter inputs (engine torque and transmission clutch dis-/engagement control) to achieve the best fuel efficiency and driveability. Once optimized via computer simulation, the schedule of inputs may be applied to a vehicle in hopes of achieving essentially the same effect with no measurements of the system torque values and no further optimizations required. The success or failure of such a strategy hinges on the *generalization* of the optimized result to different operating conditions and vehicles. Though not mathematically guaranteed, such generalization is likely if the initial parameter and input schedule optimizations were performed on a sufficiently large ensemble of representative operating conditions.

The adjoint approach for parameter identification begins with the definition of a cost function that represents the design objective. The first term of this cost function is a weighted penalty of the error between the model output $C\mathbf{q}(t)$ and the measured data $\mathbf{y}(t)$. The second term is a weighted penalty of the deviation of the (unknown) initial conditions $\mathbf{q}_o$ from any available measurements of these initial conditions, $\mathbf{y}_o$. The third term is a weighted penalty of the deviation of the parameter values θ from any approximate known "reference" values for these parameters, $\bar{\theta}$. The relative influence of all three of these terms may be adjusted by adjusting the weighting matrices Q, R_o, and $\bar{R}$.

$$\mathcal{J}=\frac{1}{2}\int_0^T(C\mathbf{q}-\mathbf{y})^*Q(C\mathbf{q}-\mathbf{y})\,dt+\frac{1}{2}(C_o\mathbf{q}_o-\mathbf{y}_o)^*R_o(C_o\mathbf{q}_o-\mathbf{y}_o)+\frac{1}{2}(\theta-\bar{\theta})^*\bar{R}(\theta-\bar{\theta}).$$

We achieve the desired model of the system when this function is minimized with respect to the uncertain parameters θ and the uncertain initial conditions $\mathbf{q}_o$ being sought, subject to the constraint

$$\dot{\mathbf{q}}=G(\mathbf{q},\theta,\phi,\psi),\quad 0<t<T,\quad \mathbf{q}=\mathbf{q}_o\ \text{at}\ t=0, \tag{5}$$

which represents the nonlinear equation relating the system state $\mathbf{q}$ to the parameters θ, the control inputs ϕ, the exogenous inputs ψ, and the initial condition $\mathbf{q}_o$. Let $\{\theta',\mathbf{q}_o'\}$ be a small variation of $\{\theta,\mathbf{q}_o\}$. By the state equation (5), this perturbation drives a small perturbation $\mathbf{q}'$ to the state $\mathbf{q}$ in the mathematical model. Defining $\mathcal{L}\mathbf{q}'\triangleq(\partial/\partial t-A)\mathbf{q}'$ as the linearization of (5) about the trajectory $\mathbf{q}(\theta,\mathbf{q}_o,\phi,\psi)$, the perturbation $\mathbf{q}'$ is found to be governed by

$$\mathcal{L}\mathbf{q}'=B_\theta\theta',\quad 0<t<T,\quad \mathbf{q}'=\mathbf{q}_o'\ \text{at}\ t=0, \tag{6}$$

which has an associated perturbation to the cost

$$\mathcal{J}'=\int_0^T(C\mathbf{q}-\mathbf{y})^*QC\mathbf{q}'\,dt+(C_o\mathbf{q}_o-\mathbf{y}_o)^*R_oC_o\mathbf{q}_o'+(\theta-\bar{\theta})^*\bar{R}\theta' \tag{7}$$

The relationship between this cost perturbation and the perturbations $\{\theta',\mathbf{q}_o'\}$ which drive it gives gradient information which is valuable in minimizing the cost function with respect to θ and $\mathbf{q}_o$. To determine this relationship, introduce the inner product $\langle\mathbf{r},\mathbf{q}'\rangle=\int_0^T\mathbf{r}^*\mathbf{q}'\,dt$ and consider the identity

$$\langle\mathbf{r},\mathcal{L}\mathbf{q}'\rangle=\langle\mathcal{L}^*\mathbf{r},\mathbf{q}'\rangle+\mathbf{b}, \tag{8}$$

where $\mathbf{r}$ is the adjoint state, $\mathcal{L}^*\mathbf{r}=(-\partial/\partial t-A^*)\mathbf{r}$, and $\mathbf{b}=[\mathbf{r}^*\mathbf{q}']_{t=T}-[\mathbf{r}^*\mathbf{q}']_{t=0}$. We now define a convenient adjoint equation, driven by the model validation error, such that

$$\mathcal{L}^*\mathbf{r}=C^*Q(C\mathbf{q}-\mathbf{y}),\quad 0<t<T,\quad \mathbf{r}=0\ \text{at}\ t=T. \tag{9}$$

Substituting the adjoint equation (9) and the perturbation equation (6) into the identity (8) and using the resulting expression to simplify the cost perturbation (7) gives an alternative expression for $\mathcal{J}'$ of the form

$$\mathcal{J}' = \left[\int_0^T B_\theta^* \mathbf{r}\, dt + \bar{R}(\theta - \bar{\theta})\right]^* \theta' + \left[C_o^* R_o (C_o \mathbf{q}_o - \mathbf{y}_o) + \mathbf{r}(0)\right]^* \mathbf{q}_o'.$$

As θ' and $\mathbf{q}_o'$ are arbitrary, the desired gradients of the cost function may be determined as simple functions of the adjoint field defined in (9):

$$\frac{\mathcal{DJ}}{\mathcal{D}\theta} = \int_0^T B_\theta^* \mathbf{r}\, dt + \bar{R}(\theta - \bar{\theta}), \quad \frac{\mathcal{DJ}}{\mathcal{D}\mathbf{q}_o} = C_o^* R_o (C_o \mathbf{q}_o - \mathbf{y}_o) + \mathbf{r}(0).$$

In terms of the notation used in this adjoint analysis, $\mathbf{q}$ and ϕ in (3) are defined as:

$$\mathbf{q} = (\bar{N}_f \;\; \bar{N}_t)^*, \quad \phi = (\bar{\Upsilon}_f \;\; \bar{\Upsilon}_p)^*, \quad \psi = (\bar{N}_p).$$

When the subsystems in (3) & (4) are combined, $\mathbf{q}$ and ϕ are defined as:

$$\mathbf{q} = (\bar{N}_f \;\; \bar{N}_t \;\; \bar{N}_p \;\; \bar{\Upsilon}_{p1} \;\; \bar{\Upsilon}_{p2} \;\; \bar{\Upsilon}_p)^*, \quad \phi = (\bar{\Upsilon}_f \;\; \bar{\Upsilon}_{c0} \;\; \bar{\Upsilon}_{c1})^*.$$

The overbar indicates that the torque variables are normalized to the maximum propeller shaft torque scale and the speed variables are normalized to the maximum engine speed scale. The computer implementation of the algorithm for identifying these 2 subsystem models includes a standard line minimization algorithm to scale each gradient-based update to $\{\theta, \mathbf{q}_o\}$.

To verify the capability of this adjoint-based model parameter identification scheme, the 18 parameters in the torque converter subsystem state equation in (3) and the 38 parameters in the torque converter and transmission system state equations, (3) & (4), are identified for the physical system undergoing a 1-2 upshift during a constant 30% driver demand maneuver. For the 18 parameters in (3), the cost is evaluated with error of the simulation model output from each of 10 sets of different measurements for the same maneuver. Successful convergence to the 18 parameters that satisfy this system identification performance objective guarantees that the model tolerates, at least, the variability of inputs exemplified by the set of 10 samples for the operation of interest. Figure 2 shows this result. The dotted lines in the top 3 plots are the inputs from one data set out of the ensemble of 10 data sets used to identify the 18 parameters. The solid lines in these plots are the inputs from yet another data set, different from any of the 10 used in the model identification. The 4th plot shows the model outputs from the identification process. The 5th, bottom, plot shows the model outputs from the validation process. The dotted lines in the 4th and 5th plots are the engine and turbine speed measurements; the solid lines are the model engine and turbine speed outputs.

The identification of the 38 parameters in the combine system (3) & (4) appears to be a significantly more difficult

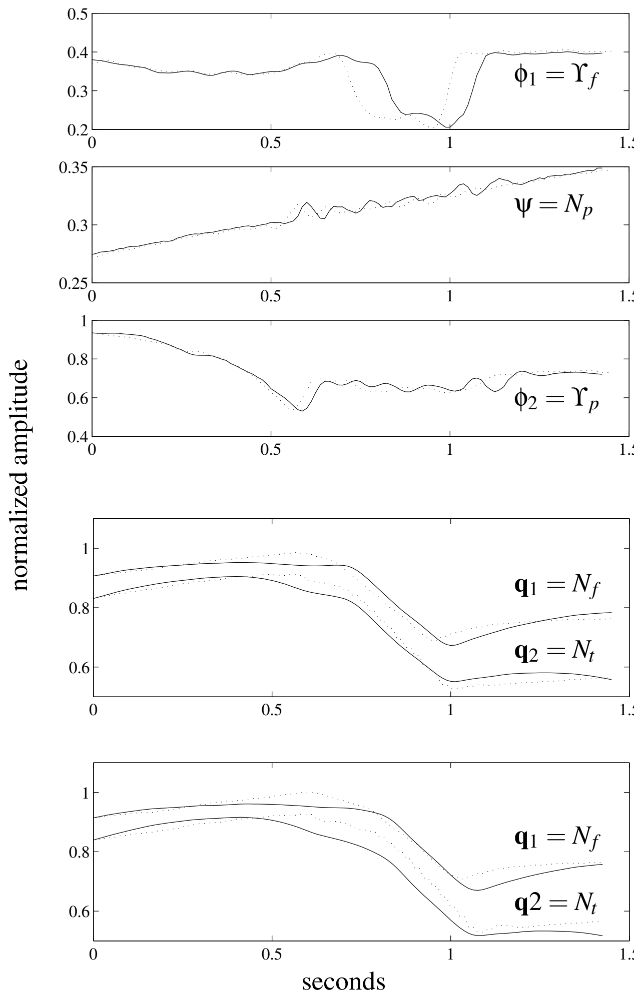

Figure 2: Inputs and outputs for the generally identified torque converter model with 18 parameters

problem. Inherent stochastic features of the transmission hydraulic system hardware prohibits it from being identified generally as a deterministic 3rd order linear dynamical model. Figure 3 shows the accurate identification for the 38 parameters in a single instance of the 1-2 upshift maneuver. The dotted lines are measurements and the solid lines are the identified model outputs in comparison.

4 Adjoint-based control optimization

Despite the failure to identify a general state equation for the combined torque converter and transmission 1-2 shift response, the accurately identifed model for the single instance of such an operation is exercised in the feedforward controller design. The adjoint analysis approach to the control input design problem is documented in [2]. Akin to the system identification process derived in section 3, a cost functional must first be defined to quantify the controlled system performance objectives. A meaningful objective for the torque converter is to maximize its efficiency. Since the turbine torque is not an accessible signal, an equivalent objective is to maximize the power transfer efficiency. Given

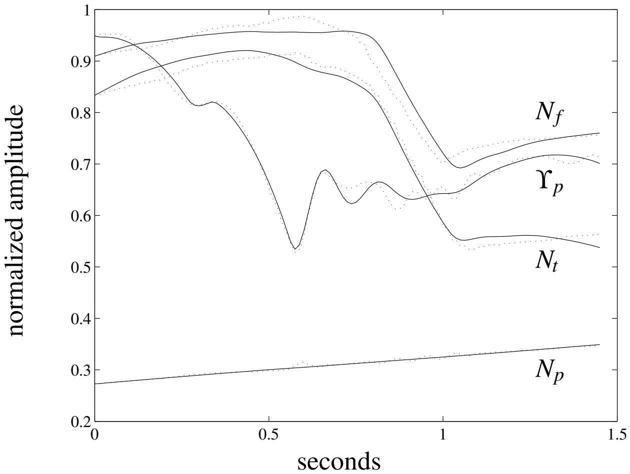

Figure 3: Outputs for the model that combines (3) and (4) with 38 parameters identified to a single data set

that the power efficiency is defined by

$$\eta = \frac{N_p \Upsilon_p}{N_f \Upsilon_f} \tag{10}$$

maximizing η can inadvertently produce undesirable torque or speed responses that compromise driveability. To satisfy the intended performance criteria, besides imposing the model state equation, 2 of the 4 factors that comprise the power transfer efficiency are targetted. Minimizing the transmission output torque fluctuations maintains driveability. Minimizing the engine torque fluctuations minimizes input disturbances to the transmission gear shift control system. Additionally, maximizing the powertrain speed ratio, $\bar{N}_p/\bar{N}_f$, reduces energy loss during the gear shift. Commensurate with all of these objectives, the powertrain torque ratio, $\bar{\Upsilon}_f/\bar{\Upsilon}_p$, should reach a setpoint specific to the 1-2 upshift.

A tractable cost function which incorporates these performance objectives is simply a penalty term on augmented model outputs. Specifically, we formuate auxiliary states that can be directly compared to the performance target. Let

$$\mathbf{q} = \left(\bar{N}_f \quad \bar{N}_t \quad \bar{N}_p \quad \bar{\Upsilon}_{p1} \quad \bar{\Upsilon}_{p2} \quad \bar{\Upsilon}_p \quad \bar{\Upsilon}_f \quad \frac{\bar{N}_p}{\bar{N}_f} \quad \frac{\bar{\Upsilon}_f}{\bar{\Upsilon}_p} \quad \frac{\bar{N}_p \bar{\Upsilon}_p}{\bar{N}_p \bar{\Upsilon}_f} \right)^*$$
$$\phi = \left(\dot{\bar{\Upsilon}}_f \quad \bar{\Upsilon}_{c1} \right)^*, \quad \psi = \left(\bar{\Upsilon}_{c0} \right). \tag{11}$$

Practically, the disengaging gear shift device actuator has little to no authority in changing the transmission dynamics and is considered an exogenous input in this model state realization. The augmented state space form also renders the engine torque a state and its time derivative the control input. Hence, the cost function reduces to to the form

$$\mathcal{J} = \frac{1}{2} \int_0^T (C\mathbf{q} - \mathbf{s})^* Q (C\mathbf{q} - \mathbf{s}) \, dt, \tag{12}$$

where $C\mathbf{q} = \left(\bar{\Upsilon}_p \quad \bar{\Upsilon}_f \quad \frac{\bar{N}_p}{\bar{N}_f} \quad \frac{\bar{\Upsilon}_f}{\bar{\Upsilon}_p} \quad \frac{\bar{N}_p \bar{\Upsilon}_p}{\bar{N}_p \bar{\Upsilon}_f} \right)^*$, and Q is now the weight that penalizes the output deviation from the desired setpoints $\mathbf{s}$.[2] The control effort is indirectly penalized through minimizing fluctuations in the new engine torque state, $\mathbf{q}_7$.

Figure 4 shows the adjoint-based optimized control input in comparison to the experimental data. The dots are the experimental data; the dashed-dotted line is an arbitrary initial guess input that began the optimization search routine; the solid line is the optimized inputs. The optimal control inputs differ only slightly from the initial guess but the change produces significantly different outputs, demonstrating that the model is highly sensitive.

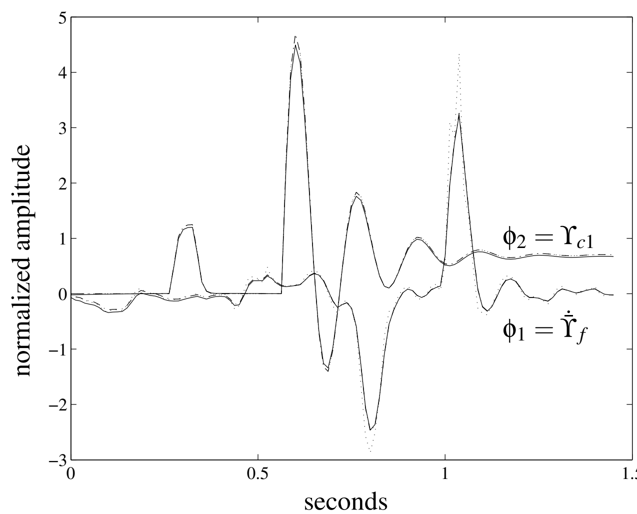

Figure 4: Control input optimization results for the identified model in (3) and (4) in comparison to the experiment

Figure 5 compares some of the model states (solid line), to the experimental data (dotted line), and the same states from the arbitrary initial guess input (dot-dashed line) that started the optimization search routine. The setpoints for the output states are also plotted to gauge performance. The results show that despite the highly sensitive model, measurable improvements are gained.

5 Conclusions

In this investigation, we have shown that adjoint analysis can be used as a powerful tool for designing multiple input-multiple output open-loop or feedforward nonlinear time varying control trajectories as well as identifying nonlinear system model parameters. The fairly successful employment of both these techniques to a constant demand 1-2 upshift in a vehicle suggests the applicability of this strategy in both modeling and controlling the powertrain, to other driving maneuvers, and to other advanced power transfer technologies. The benefit of the adjoint-based optimization algorithm is its remarkable computational efficiency when the number of parameters, inputs, and output are large. The failure of the present effort to identify a general model for the combined torque converter and transmission system might be overcome in the future by devising a

[2] In general, the setpoints can be time varying. They are constant here.

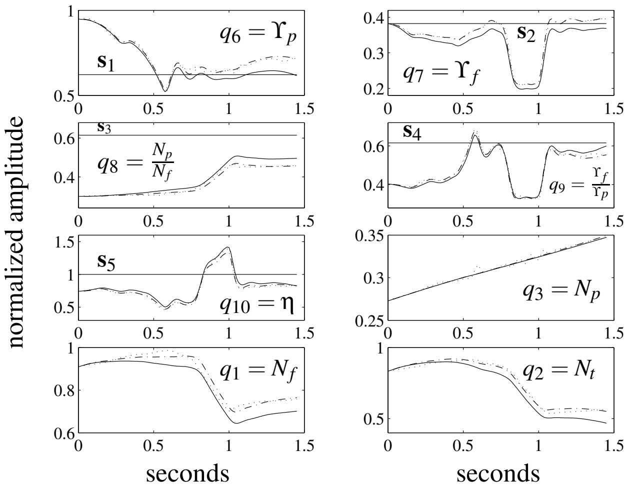

Figure 5: States and outputs from the identified model in (3) and (4) given the inputs from figure 4 compared to the performance objectives and the experiment

more comprehensive model structure that accounts for other variations of the system which are not currently captured by the present model. Once a representative system model is established, its parameters can be identified, and the control input optimization problem may again be revisited. Exercising this optimization process can provide improvements in subsystems control and integration, as well as, new insight for chosing control objectives that appropriately reflect the performance requirements.

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