

Optimal Operation of a Turbocharged Diesel Engine during Transients

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ABSTRACT

Recent development has renewed the interest in drivetrain concepts which give a higher degree of freedom by disconnecting the engine and vehicle speeds. This freedom raises the demand for active control, which especially during transients is not trivial but of which the quality is crucial for the success of the drivetrain concept. In this work the fuel optimal solution for a turbocharged diesel engine connected to a load which does not restrict the engine speed is derived, analysed and utilized for finding a suboptimal operating point trajectory. We use a Willans efficiency model for the engine, expanded with a first order delay dependent torque reduction representing the turbocharger pressure, and study different output power transients. The analysis is made with dynamic programming, Pontryagin's maximum principle and a suboptimal strategy based on the static optimal operating points. We present a method for using Pontryagin's maximum principle for deriving the optimal operating point trajectory. The time needed for computation was reduced a factor >100 compared to dynamic programming, but this method is only applicable to load cases with steps between different high output powers. We also present a suboptimal method which shows a <1% increase in fuel consumption compared to the optimal, while reducing the time needed for computation a factor >1000 compared to dynamic programming.

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INTRODUCTION

BACKGROUND AND MOTIVATION

Faster, smaller and cheaper computers have created the opportunity for more intricate control of mechanical systems, or even introduction of new mechanical solutions that would be infeasible without a high level of control. In the field of vehicle engineering this can be seen in the recent diversification of drivetrain architectures [1]. The motivation for altering the drivetrain is often reduced fuel consumption, for environmental or economical reasons. The fuel consumption is highly dependent on the driving cycle in which the vehicle operates [2]. For wheel loaders there is no standardized driving cycle, but it is clear that common wheel loader operation is characterized by a highly transient power requirement [3]. This is exemplified by the recorded and scaled engine output power trajectory presented in Figure 1. This motivates analysis of the optimal engine operation during transients. The drivetrain of the reference vehicle, in which the recording was made, consists of a diesel engine, a torque converter and an automatic gearbox. This solution has the advantage that it is mechanically robust since the torque converter provides some disconnection of the wheels from

the engine, and that it automatically adapts to changes in torque. The drawback is that there is always some slip in the converter, which reduces efficiency.

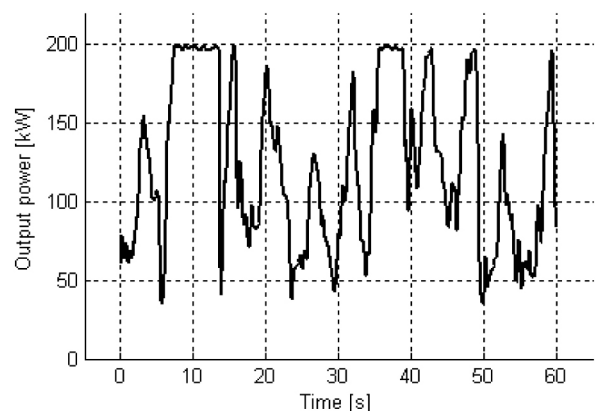


Figure 1. Recorded engine output of a wheel loader

There have been some work done on advanced wheel loader transmission control, but mainly in the fields of low level actuator control [4], autonomous vehicles [5] [6], and hybrid electric powertrains with heuristic controls [7] [8]. There is also a vast amount of research on advanced on-road

passenger vehicle drive trains. Most of these use heuristic control laws [9] [10] or some variant of the ECMS approach [11] [12]. Apart from these, there are articles such as [13] and [14] in which the optimal trajectory is derived, but the analysis could well be extended. In [15] a thorough investigation of the optimal solution is made, but only for a fully stochastic future load. There are several reasons for studying the optimal trajectory of vehicle operation, even though direct application of the solution would require perfect prediction of future operating conditions. In the case of hybrid electric vehicles with a simplified battery model, the optimization results in a single cycle specific parameter which can be used in a causal controller, this is known as the ECMS [16]. Since it generally is optimal to operate at a stationary point during static conditions, the online optimization will in general only require prediction at transients, and then with a short horizon. Some proposals on how to achieve this can be found in [17] [18] [19]. In case the vehicle is made autonomous, as proposed by [5] [6], the controller may also inform the optimizer about upcoming actions. The extremely transient operation of wheel loaders, along with new possibilities of realizing optimal operation, motivates further examination of optimal trajectories during transients.

PROBLEM OUTLINE

Transmissions such as CVTs and hydrostatic and electric drives enable a free selection of engine speed, and thereby potentially higher overall efficiency. Due to the diversity of configurations proposed it is not possible to make a general analysis that includes any detail of the transmission itself. We assume that such a drivetrain can be approximately divided into one power producing and one power consuming part. In a series hybrid this partitioning would be done in the electric connection. The power consumption is then defined by the driving cycle and efficiencies only on the power consuming side of the drivetrain. The driving cycle can therefore, for control optimization purpose, be reduced to a power demand trajectory.

On the power producing side, it is not possible to instantly switch between static optimal operating points both because the engine inertia restricts engine speed change and because the turbocharger inertia restricts engine torque change. Without prediction we would need to introduce a penalty for deviating from desired output power, and this penalty function would have an impact on the optimal solution, thereby obscuring the mechanisms behind the true optimal trajectory. Because of this we assume perfect prediction of power demand and require perfect following of this. Since transient output power is of fundamental importance in wheel loader operation, the goal of this paper is to gain deeper understanding of the mechanisms behind the fuel optimal solution to power transients.

PROBLEM

DRIVETRAIN SETUP

The system consists of a turbo-charged diesel engine connected to a load which allows for a free choice of engine speed, such as an electric generator. The engine is modeled as an inertia and a static Willan's efficiency model, and the turbocharger is modeled as a first order delay which causes an output torque reduction. The actual Willan's and turbo parameters are based on a highly simplified wheel loader engine in the 250kW maximum output power range.

PROBLEM STATEMENT

The problem studied in this paper is the minimization of total amount of fuel, or fuel energy, consumed during a driving mission specified by the output power trajectory. We express this as minimizing the integral of the fuel power

$$\min_{m_f(t)} \int_0^T P_{m_f} dt \quad (1)$$

The engine output power trajectory is assumed to be known. Based on this, the optimal engine operating point trajectory is derived. The problem is solved with dynamic programming and analyzed with Pontryagin's maximum principle, and a suboptimal method for following the output power trajectory is presented. The load cases we use are engine output power steps and the recorded output power trajectory that was presented in Figure 1.

ENGINE AND TURBO-CHARGER MODEL

The engine is modeled as an inertia which is affected by the engine torque and a load torque. The load is defined by the externally specified output power trajectory. We also have a lower bound of 800rpm on the engine speed.

$$\frac{d\omega_e(t)}{dt} I_e = T_e(t) - \frac{P_{load}(t)}{\omega_e(t)} \quad (2)$$

From here on the t dependency will be omitted in the equations. The relation between the injected fuel and the engine torque is described by the Willan's efficiency model [20] with an additional torque loss caused by a lack of turbocharger pressure

$$T_e = e \cdot A \cdot m_f - T_{loss} - T_{pt} \quad (3)$$

In which m_f is fuel mass per injection, ω_e is engine speed, T_{pt} is torque loss caused by low intake pressure and

$$A = \frac{q_{lthv} n_{cyl}}{2\pi n_r} \quad (4)$$

$$e = e_0 - e_1 m_f \quad (5)$$

$$e_0 = e_{00} + e_{01}\omega_e + e_{02}\omega_e^2, \quad e_1 = e_{10} + e_{11}\omega_e \quad (6)$$

$$T_{loss} = T_{loss0} + T_{loss2}\omega_e^2 \quad (7)$$

The turbocharger is modeled as a first order delay for the intake air pressure

$$\frac{dp(t)}{dt} \tau(\omega_e) = p_{set}(\omega_e, m_f) - p(t) \quad (8)$$

in which p is the intake air pressure and

$$p_{set} = a_1\omega_e + a_2m_f + a_3, \quad \tau = \tau_1\omega_e + \tau_2 \quad (9)$$

Henceforth the t dependency will be omitted. The torque loss due to low intake pressure is described by

$$T_{pt} = k_1(\omega_e)(p - p_{set})^2 - k_2(\omega_e)(p - p_{set}) \quad (10)$$

$$k_1 = k_{11}\omega_e + k_{12}, \quad k_2 = k_{21}\omega_e + k_{22} \quad (11)$$

The system efficiency e_{tot} is defined as the mechanical output power divided by the fuel input power

$$e_{tot} = \frac{P_e}{P_{mf}} = \frac{T_e\omega_e}{\omega_e A m_f} = e_0 - e_1 m_f - \frac{T_{loss} + T_{pt}}{A m_f} \quad (12)$$

With this notation the objective function (1) can be written as

$$\min_{m_f(t)} \int_0^T A \omega_e m_f dt \quad (13)$$

METHOD

STATIC OPTIMIZATION

The first step in analyzing optimal operation of engines is to derive the static optimal operating line of the engine. In static conditions $p = p_{set} \Rightarrow T_{pt} = 0$, which means that the turbo model will not affect the static optimization. We numerically solve

$$\max_{m_f} e_{tot}(P_{load})$$

$$\frac{d\omega_e}{dt} = \frac{dp}{dt} = 0, \quad \omega_e \geq 800 \text{rpm} \quad (14)$$

for loads in the range $0 < P_{load} < 250 \text{kW}$. We denote the solution the static optimal operating point, or (SOOP), corresponding to each P_{load} .

DYNAMIC PROGRAMMING

Dynamic programming is a well known method for optimizing processes that guarantees global optimum. The variant used here is as follows; denote the discretized state (ω_e, p) , X , the control (m_f) , U and the time t_k with $k=0, N$. In the state, control and cost J , the index k means (t_k) . The dynamic programming algorithm [21], [22] can then be formulated as:

1. For $x_N \in X_N$, declare $J(x_N) = J_N$
2. **for** $k = N - 1, \dots, 1$ **do**
3. For $x_k \in X_k$, simulate (2) and (8) for t_k to t_{k+1} for all $u \in U$ to find $x_{k+1}(x_k, u)$
4. For $x_k \in X_k$, calculate $J(x_k) = \min_{u \in U} (A x_k u dt + \tilde{J}(x_{k+1}))$, where $\tilde{J}(x_{k+1})$ is interpolated from $J(x_{k+1} \in X)$
5. **end for**
6. Select an initial state $\hat{x}_0 = x_0$
7. **for** $m = 1, \dots, N$ **do**
8. For $\hat{x}_{m-1}$, simulate (2) and (8) for t_{m-1} to t_m for all $u \in U$ to find $x_m(\hat{x}_{m-1}, u)$
9. Select $\hat{u}_m = \text{argmin}_{u \in U} (A \hat{x}_{m-1} u dt + \tilde{J}(x_m))$, where $\tilde{J}(x_m)$ is interpolated from $J(x_m \in X)$ and $\hat{x}_m = x_m(\hat{x}_{m-1}, \hat{u}_m)$
10. **end for**

The resulting $\hat{x}(t_k)$, $\hat{u}(t_k)$ is then the optimal trajectory when starting at x_0 . In this work the simple final cost

$$J_N = \begin{cases} 0 & \text{if } X_N \in (\omega_e(N) \geq \omega_{lim}, p(N) \geq p_{lim}) \\ \infty & \text{else} \end{cases} \quad (15)$$

has been used. This method is simple to understand, nonlinearities such as state bounds are easily handled, and the method guarantees global optimum. The drawback is that the method is computationally heavy since the number of simulations in step 3 grows rapidly with the number of states and the density of the discretization. The number of simulations is $N \cdot s(U) \cdot s(X)$, where s denotes size of discretization. If U and/or X have more than one dimension s is the size of the discretization in each dimension multiplied. In this case U has one dimension and X has two dimensions. It is clear that the control and time discretization cannot be too sparse if the continuous-space optimal solution is to be closely approximated. The success of the interpolation in steps four and nine depends on the size of J_k and the shape of $J(x_k)$. In this problem J_k goes to infinity for high output power combined with low engine speed and/or low intake