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An Equivalent Consumption Minimisation Strategy based on 1-Step Look-Ahead Stochastic Dynamic Programming ⋆

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Abstract: In this paper, a systematic procedure to determine the equivalence factor in the equivalent consumption minimisation strategy (ECMS) is proposed. This is relevant when ECMS is not only used for controlling the power split between the internal combustion engine and the electric machine of a hybrid electric vehicle (HEV), but also for controlling several auxiliary systems. In this case, the number of controlled components and energy buffers increases, which causes the number of tunable equivalence factors to increase. The procedure to determine the equivalence factors proposed in this paper is based on the observation that ECMS can be considered as a time-invariant feedback policy and dynamic programming (DP) also yields a time-invariant feedback policy when the time horizon of the control problem approaches infinity and the disturbances are constant or absent. As the drive cycle can be considered as a (stationary stochastic) disturbance, we propose to formulate ECMS as the solution of a 1-step look-ahead stochastic dynamic program (1slSDP). This strategy results in an energy management strategy that performs close to optimal and yields similar fuel consumption results, when compared to a well-tuned ECMS. The absence of any parameters to be tuned and the fact that fuel consumption is similar to a well-tuned ECMS makes 1slSDP a useful strategy for energy management of HEVs.

Keywords: Hybrid Electric Vehicle, Energy Management, Stochastic Dynamic Programming, Equivalent Consumption Minimisation Strategy.

1. INTRODUCTION

Measures to reduce fuel consumption are an important topic of research in the automotive field due to the depletion of fossil fuels and increasingly stringent regulations on pollutant emissions. The most well-known measure for fuel consumption reduction in vehicles is hybrid technology. In hybrid electric vehicles (HEVs), the fuel consumption is reduced by smart control of the power split between the internal combustion engine and the electric machine connected to a high-voltage battery. This technology improves the efficiency of the propulsion system. The fuel consumption, however, is not only affected by the propulsion system. Particularly for heavy-duty vehicles, a significant amount of power, and hence fuel, is consumed by auxiliary systems, such as a refrigerated semi-trailer, an air supply system and coolant systems. Their power request is often variable and this offers opportunity to optimise the power request over time. Each of these auxiliaries introduces at least one state and decision variable to the energy management system. For example, some state variables that can be considered are the energy in the battery, the temperature in a refrigerated semi-trailer, the air pressure in the air supply system and the temperature of the after-treatment system. Finding a strategy that determines the optimal power flows inside a HEV with multiple auxiliaries requires solving an optimal control problem, which becomes harder when the number of auxiliaries increases.

Finding effective methods for solving the optimal control problem encountered in energy management has been a subject of recent research.

For the optimal control problems found in energy management, typically two approaches are used: dynamic programming (DP) and the equivalent consumption minimisation strategy (ECMS). In case the entire drive cycle is known a priori, the optimal solution can be determined with DP (Sciarretta and Guzzella, 2007). The obtained result is optimal, but the strategy cannot be used in real-time due to computational burden and because the entire drive cycle is typically not known a priori. To overcome this problem, feedback strategies like ECMS are used (Onori and Serrao, 2011; Serrao et al., 2009). ECMS was originally developed for HEVs with a simple power split between the internal combustion engine and the electric machine connected to a high-voltage battery. By means of an equivalence factor, the equivalent fuel consumption for electric energy is compared to the fuel consumption of the engine in the fuel consumption minimisation problem. This results in an online strategy, which requires only the equivalence factor to be determined.

In the literature, several methods exist for online determination of the equivalence factor. Even though all these methods require tuning, this tuning is well understood and extensively studied for the power-split problem of a HEV. In particular, the equivalence factor can be adapted by using drive-cycle prediction methods, driving pattern recognition methods, and following a reference for the

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energy in the battery based on a proportional-integral controller, see, e.g., (Onori and Serrao, 2011; Sciarretta and Guzzella, 2007; Jager et al., 2013) and references therein. Integrating additional components in the energy management system adds more equivalence factors in ECMS. This has been done for battery aging (Serrao et al., 2011), thermal management of the engine (Lescot et al., 2010), the after-treatment system (Kessels et al., 2010) and a waste-heat recovery system (Merz et al., 2012). Typically, the equivalence factors in these papers are tuned heuristically so that constraints are not violated. Since all components of a powertrain interact and the number of equivalent factors increases when the number of components in the energy management problem increases, tuning becomes increasingly more difficult.

To mitigate the extensive tuning of the equivalence factors in ECMS, this paper proposes a systematic procedure to determine these equivalence factors. The procedure is based on the observation that DP yields a time-invariant feedback controller when the time horizon of the control problem approaches infinity and the disturbances are constant or absent. Therefore, an ECMS is considered as a result of a so-called 1-step look-ahead stochastic dynamic program (1slSDP). In this case, the disturbances are not constant, but assumed to satisfy a stationary random process, as was done in (Moura et al., 2010). The proposed energy management system achieves a fuel consumption close to optimal and approximately the same compared to a well-tuned ECMS, while it does not require tuning of equivalence factors. Moreover, the proposed strategy can handle multiple auxiliaries in the same systematic way, in contrast to ECMS. The strategy has been simulated by applying energy management to a hybrid electric truck with a refrigerated semi-trailer.

The remainder of this paper is organised as follows. First, the existing and the proposed solution methods are presented in Section 2. In Section 3, the case study is described. Finally, Section 4 presents the simulation results and conclusions are drawn in Section 5.

2. SOLUTION METHODS

In this section, the energy management problem is given and the solution methods for this problem are described. Moreover, a new method based on stochastic dynamic programming is proposed at the end of this section.

2.1 Problem Description

In energy management systems, optimal control problems of the following form are encountered

$$\min_{u(t)\in\mathcal{U}} \int_0^{t_f} g(x(t), u(t), w(t))\mathrm{d}t \tag{1a}$$

subject to

$$\dot{x}(t) = f(x(t), u(t)), \tag{1b}$$

$$x(t) \in \mathcal{X} \subset \mathbb{R}^n, \tag{1c}$$

for some $x(0)$ and $w(t)$ where $t \in [0, t_f]$. In energy management, the objective function g typically corresponds to the fuel consumption of the internal combustion engine. The decision variable u represents the controllable inputs of the components related to the energy flows in the vehicle, the disturbance w represents the information of the to-be-completed drive cycle, which is typically given by either torque or power, and angular velocity of the wheels or engine, and x is the state of the system with n the number of states. The state x typically consists of the battery energy, temperatures in a refrigerated semi-trailer or after-treatment system, the air pressure in an air supply system and so on, and satisfies a differential equation (1b) and is constrained to satisfy (1c) for some compact set $\mathcal{X}$ defined by, e.g., the energy limits of the battery, temperature limits of the air in the refrigerated semi-trailer and air pressure limits of the air supply system. The decision variable u is constrained to satisfy a compact set $\mathcal{U}$ defined by, e.g., the maximum and minimum power flowing into and out of the battery.

To solve problem (1), DP, stochastic DP (SDP) or an ECMS can be used. These methods will briefly be explained and it is shown how these methods are related. This relation allows the proposal of a systematic way of determining the equivalence factor encountered in ECMS.

2.2 Dynamic Programming

When w is known a priori, the optimal control problem (1) can be solved using DP. The solution (in continuous time) involves solving the Hamilton-Jacobi-Bellman (HJB) equation (Bertsekas, 2005), given by

$$\min_{u\in\mathcal{U}}\{g(x, u, w(t)) + \tfrac{\partial J(t,x)}{\partial t} + \tfrac{\partial J(t,x)}{\partial x} f(x, u)\} = 0 \tag{2}$$

with $J(t_f, x) = 0$, for all $x \in \mathcal{X}$, $t \in [0, t_f]$, with f and g as defined in (1) and J as the optimal cost-to-go function of the problem. In case the cost-to-go function is not differentiable, it is not possible to obtain a solution for the HJB-equation in the classical sense of a solution and generalised solutions (such as viscosity solutions) are needed. The minimiser of (2) yields the optimal control policy, i.e.,

$$u^*(t, x) = \arg\min_{u\in\mathcal{U}}\{g(x, u, w(t)) + \tfrac{\partial J(t,x^*)}{\partial x} f(x, u)\} \tag{3}$$

for all $x \in \mathcal{X}$. If the obtained optimal control policy is applied, the solution to the problem is optimal. Due to the fact that the solution depends on w, it can only be calculated when $w(t)$ is known for all $t \in [0, t_f]$. As such, DP is an offline method.

2.3 Equivalent Consumption Minimisation Strategy

A second solution strategy that is commonly used in energy management is the ECMS. The idea of ECMS is to relate the change in energy in the energy buffers given by $f(x, u)$ to an equivalent fuel consumption and minimise the sum of the instantaneous fuel (power) consumption and the fuel (power) equivalent consumption. The close to optimal solution of (1) obtained with ECMS is given by

$$u^*(x, w) = \arg\min_{u\in\mathcal{U}}\{g(x, u, w) + \lambda^T f(x, u)\} \tag{4}$$

with g and f as in (1). Since only the instantaneous cost is minimised, the strategy does not require w to be known for all t. Even though the obtained control policy is not optimal, it is a feedback policy and is therefore an online strategy.