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IFAC-PapersOnLine 48-15 (2015) 203–208

# Receding Horizon Control for Distributed Energy Management of a Hybrid Heavy-Duty Vehicle with Auxiliaries ⋆

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**Abstract:** In this paper, a real-time and distributed solution to Complete Vehicle Energy Management (CVEM) is presented using a receding control horizon in combination with a dual decomposition. The dual decomposition allows the CVEM optimization problem to be solved by solving several smaller optimization problems. The receding horizon control problem is formulated with variable sample intervals, allowing for large prediction horizons with only a limited number of decision variables and constraints. The receding horizon control problem is solved for a case study of a hybrid heavy-duty vehicle, equipped with a high-voltage battery system and a refrigerated semi-trailer. Simulations demonstrate that close to optimal performance in terms of fuel consumption is obtained. The average execution time is 11.4 ms demonstrating that the proposed solution method is indeed real-time implementable.



*Keywords:* Optimal control, Energy management system, Receding horizon control, Distributed control, Predictive control, Hybrid Electric Vehicles

## 1. INTRODUCTION

Hybrid technology enables vehicles to make a powersplit between the primary power device, e.g., an internal combustion engine and the secondary power device, e.g., an electric machine, so that the fuel consumption can be reduced. However, the power flows in the vehicle are not limited to the propulsion system only. Particularly for heavy-duty vehicles, a significant amount of power is consumed by auxiliary systems, such as a refrigerated semi-trailer, an air supply system and coolant systems. As global efficiency at vehicle level is not guaranteed by optimizing each of the components separately, energy management needs to be done on a complete vehicle level. We refer to this desired energy management strategy as Complete Vehicle Energy Management (CVEM), see (Kessels et al., 2012). Behavior of each auxiliary component is generally unique and each auxiliary adds at least one state and decision variable to the CVEM problem. Examples of state variables include temperature in the refrigerated semi-trailer, air pressure in the air supply system and temperature of the fluid in the engine coolant system.

Well-known real-time methods for energy management are equivalent consumption minimization strategies (ECMS) with various adaptive mechanisms based on drive cycle prediction, driving patterns recognition and state-of-charge feedback, see (Onori and Serrao, 2011) and the references therein. To improve anticipation on future events using road preview information, a significant amount of work can be found on methods that are based on (stochastic) Model Predictive Control (MPC), see e.g., (Di Cairano et al., 2014; Schepmann and Vahidi, 2011; Borhan et al., 2012). All aforementioned methods use a centralized control approach to solve the energy management problem for a hybrid vehicle without auxiliaries. By adding more decision variables and states to the problem, as with CVEM, the centralized controller can become computationally demanding and is not scalable without revising the complete controller.

For this reason, distributed solutions for energy management start to appear. Many interesting solutions for distributed control can be found from other fields, see e.g., (Stephens et al., 2015) for distributed energy demand side management and (Fardad et al., 2010) for optimal control of vehicle formations. The application of distributed solution methods to the CVEM problem in the automotive field is only recently starting to attract attention. In (Chen et al., 2014), a real-time implementable game-theoretic approach to CVEM is shown, where the drive cycle is only predicted over a short horizon. In (Nguyen et al., 2014), a game-theoretic approach in combination with MPC is used to arrive at a distributed solution, while real-time implementation is not considered. In (Nilsson et al., 2015), the computation is distributed using the Alternating Direction Method of Multipliers (ADMM), while ideas from ECMS are used to calculate the equivalent costs at a supervisory level. In (Romijn et al., 2014), the computation is distributed via a dual decomposition without using a supervisory level which allows drive cycle prediction to be readily taken into account.

This paper proposes a computationally efficient implementation of the method presented in (Romijn et al., 2014). The dual decomposition allows the large-scale optimiza-

⋆ This work has received financial support from the FP7 of the European Commission under the grant CONVENIENT (312314).

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Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2015.10.029

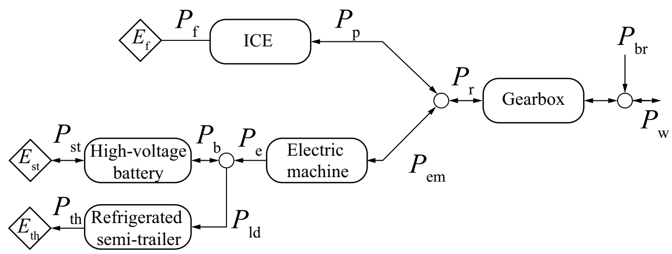


Fig. 1. Hybrid powertrain, including an internal combustion engine (ICE), an electric machine (EM), a high-voltage battery and a refrigerated semi-trailer.

tion problem to be solved by solving several smaller optimization problems. Furthermore, the approach is scalable in terms of adding components. However, CVEM, as in (Romijn et al., 2014), is solved for a relatively long horizon with a fixed sample interval, which allows computing the optimal solution for CVEM offline. This solution method is unsuitable for real-time implementation. To resolve this issue, we propose to use the receding horizon principle and apply the same dual decomposition to this problem. Computational limitations due to real-time implementation restrict the maximum allowable number of decision variables. Therefore, varying sample intervals will be used in our problem formulation to create a large prediction horizon, while having only a limited number of decision variables and constraints. The approach is similar to move blocking, see, e.g., (Cagienard et al., 2007), but is computationally less expensive due to a reduction in constraints. The receding horizon control approach in this paper is in line with distributed model predictive control, see, e.g., (Maestre and Negenborn, 2014). Owing to the problem formulation, a new implementation is proposed.

## 2. TOPOLOGY AND PROBLEM FORMULATION

We reconsider in this paper the case study of (Romijn et al., 2014), consisting of a heavy-duty hybrid vehicle that includes an internal combustion engine (ICE), an electric machine (EM), a high-voltage battery and a refrigerated semi-trailer. The topology is schematically shown in Fig. 1, in which $P_{\mathrm{f}}$ and $P_{\mathrm{p}}$ denote the ICE's fuel and mechanical power, respectively, $P_{\mathrm{e}}$ and $P_{\mathrm{em}}$ the EM's electrical and mechanical power, respectively, $P_{\mathrm{b}}$ and $P_{\mathrm{st}}$ the battery's electrical and stored chemical power, respectively, $P_{\mathrm{ld}}$ and $P_{\mathrm{th}}$ the refrigerated semitrailer's electrical and thermal power, respectively, $P_{\mathrm{br}}$ and $P_{\mathrm{r}}$ is the mechanical brake power and requested drive power, respectively and $E_{\mathrm{st}}$ denotes the battery state of energy and $E_{\mathrm{th}}$ denotes the thermal energy in the refrigerated semi-trailer.

The main objective is to minimize the predicted cumulative fuel consumption, at each time instant $k \in \mathbb{N}$, given by

$$J(k) = \sum_{\ell=1}^{n} \tau(\ell)\, \dot{m}_{\mathrm{f}}(P_{\mathrm{p}}(k+\ell-1|k)), \tag{1}$$

subject to dynamics and conversion efficiencies of the components in Fig. 1. In this expression, $n$ is the number of decision variables, $P_{\mathrm{p}}(k+\ell-1|k)$ is the predicted engine power at time instant $k+\ell-1$ using information available at time instant $k$ and $\tau(\ell) \in \mathbb{R}_+$ is a variable sample interval. In this formulation, the prediction horizon $N_{\mathrm{p}} = \sum_{\ell=1}^{n} \tau(\ell) \in \mathbb{R}_+$ can be large, without increasing the number of decision variables $n$. Note that in (Romijn et al., 2014), we had that $\tau(\ell) = 1$ for all $\ell \in \{1, \ldots, n\}$. The application of the dual decomposition to the CVEM problem with variable sample intervals remains the same and details are given in (Romijn et al., 2014). A summary of the notation, the component models and the problem formulation are given in this section.

### 2.1 Notation

The CVEM problem can be formulated as a static optimization problem, as was done in (Romijn et al., 2014). To formulate this problem over a receding horizon, we introduce the following notation:

$$\mathbf{P}_i(k) = [P_i(k|k), \ldots, P_i(k+n-1|k)]^T \in \mathbb{R}^n, \tag{2a}$$

$$\mathbf{E}_m(k) = [E_m(k+1|k), \ldots, E_m(k+n|k)]^T \in \mathbb{R}^n, \tag{2b}$$

$$\boldsymbol{\alpha}_{h,j}(k) = [\alpha_{h,j}(k|k), \ldots, \alpha_{h,j}(k+n-1|k)]^T \in \mathbb{R}^n, \tag{2c}$$

$$\boldsymbol{\tau} = [\tau(1), \ldots, \tau(n)]^T \in \mathbb{R}^n, \tag{2d}$$

for $k \in \mathbb{N}$, $i \in \{\mathrm{f, p, em, e, b, ld, st, th\,br, r}\}$, $j \in \{0, 1, 2\}$, $m \in \{\mathrm{st, th}\}$ and $h \in \{\mathrm{p, em}\}$. In this notation, $\ell|k$ denotes decisions of variables $P_i$ or predictions of states $E_m$ at (discrete) time instant $\ell$ based on information at (discrete) time instant $k$. Speed-dependent efficiency coefficients $\alpha_{h,j}(\ell|k) = f_{h,j}(\omega(\ell|k))$, are used to model the ICE and the EM, respectively, with $\omega(\ell|k)$ the predicted engine speed. It is assumed that the EM runs at the same speed as the ICE. The functions $f_{h,j}(\omega(\ell|k))$ are not part of the optimization problem because engine speed is predicted and can therefore be of any type.

Because of the variable sample interval $\tau(\ell) = t(k+\ell) - t(k+\ell-1)$, we need to revise the formulation of the energy buffer state dynamics when compared to (Romijn et al., 2014). The energy in the high-voltage battery and the refrigerated semi-trailer are represented by a first-order differential equation, i.e.,

$$\tfrac{d}{dt} E_m(t) = \tilde{A}_m E_m(t) + \tilde{B}_m P_m(t), \tag{3}$$

for $m \in \{\mathrm{st, th}\}$ and where $\tilde{A}_m$ and $\tilde{B}_m$ are scalars. This differential equation allows us to make a prediction of $E_m(k+\ell|k) = E_m(t(k+\ell))$, for a given initial condition $E_m(k+\ell-1|k) = E_m(t(k+\ell-1))$, by using the convolution integral

$$E_m(k+\ell|k) = e^{\tilde{A}_m \tau(\ell)} E_m(k+\ell-1|k) + \int_0^{\tau(\ell)} e^{\tilde{A}_m s} \tilde{B}_m P_m(t(k+\ell)-s)\, ds. \tag{4}$$

If we restrict the power $P_m$ to be piecewise constant, i.e., $P_m(k+\ell-1|k) = P_m(s)$ for $s \in [t(k+\ell-1), t(k+\ell)]$ and $\ell \in \{1, \ldots, n\}$ and define $A_m(\ell) = e^{\tilde{A}_m \tau(\ell)}$ and $B_m(\ell) = \int_0^{\tau(\ell)} e^{\tilde{A}_m s} \tilde{B}_m ds$, then expression (4) can be grouped for all $\ell \in \{1, \ldots, n\}$ and written as

$$\mathbf{E}_m(k) = \Phi_m E_m(k) + \Gamma_m \mathbf{P}_m(k), \tag{5}$$

with

$$\Gamma_m = \begin{bmatrix} B_m(1) & 0 & \ldots & 0 \\ A_m(2)B_m(1) & B_m(2) & \ddots & 0 \\ \vdots & & \ddots & 0 \\ \prod_{\ell=2}^{n} A_m(\ell)B_m(1) & \prod_{\ell=2}^{n-1} A_m(\ell)B_m(2) & \ldots & B_m(n) \end{bmatrix}, \tag{6a}$$