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Online Optimizing Plug-In Hybrid Energy Management Strategy for Autonomous Guidance and Drive-aware Scenarios

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Abstract: Recent advances in autonomous driving and vehicle connectivity help to ensure safety and comfort in various driving conditions. These trends have widenened the system boundary conditions for hybrid powertrain operation with driving trajectory planning hence offering potential to improve powertrain operational efficiency. This paper presents an energy management (EM) controller for a plug-in hybrid vehicle exploiting predicted velocity trajectory together with its integration in both autonomous longitudinal guidance and driver-aware scenarios. The driver-aware scenario uses Markov chain based stochastic modelling of driving characteristics. The proposed EM controller solves online, a discretized version of the fuel consumption minimization problem using direct methods transcribing the problem into a finite dimensional mixed boolean quadratic problem with polytopic constraints. The convex part of the resulting problem is solved using an active set method. Simulation results from different driving situations based on standard driving cycle and real world driving scenarios demonstrate the functionality of the controller and its flexbility to handle varying control objectives.

Keywords: Energy Management, Plug-in Hybrid Electric Vehicle, Model Predictive Control, Quadratic Programming, Active Set Method

1. INTRODUCTION

Rigourous regulatory requirements, customer demand for improved efficiency and increased competitiveness among vehicle manufacturers, have increased emphasis on reduction of energy consumption and equivalent CO_2 emissions in upcoming powertrain concepts. The fleet CO_2 emission target for new passenger cars and light-commercial vehicles by 2020 in the EU is set as 95 gram per km. Automobile manufacturers face challenges to devise effective CO_2 reduction measures due to demanding pollutant emission regulations retaining the requisite fun-to-drive. Further the measures shall not only be developed for legal driving cycles but also be effective in real driving operation. Three technology trends that strongly influence future mobility are powertrain hybridization, vehicle connectivity and autonomous driving. Hybridization of a conventional powertrain refers to its augmentation with an additional energy convertor and energy storage device. One possible solution which is currently favored is Plug-in Hybrid Electric Vehicle (PHEV), which is a combination of the Internal Combustion Engine (ICE) and the Electric Traction Machine (ETM) with high energy capacity battery which can be externally charged. Presence of multiple power sources increases the Degree-of-Freedom (DoF) of the hybrid propulsion unit. The supervisory control layer that uses this additional DoF to manage the power flow between ICE and ETM meeting the driver power request is termed as the Energy Management (EM) controller.

Vehicle connnectivity collectively defines the interaction between the vehicle and its environment encompassing communication between Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I). Prognosed reduction in accidents, optimization of traffic flow and new potential in individual mobility have been the motivating factors for increased attention in the field of autonomous driving. The reported fuel savings of 22% (ECOMOVE, 2009) by avoiding inefficient driving can be achieved using autonomous eco-guidance. The fuel saving potential can be further increased by combining it with efficient power split in PHEV powertrains. This paper presents a EM controller that uses the predictive information available from vehicle connectivity during autonomous guidance to manage powerflow between the energy converters of PHEV. One exemplary use-case based on connectivity is to inform the EM controller to maintain a certain battery charge reserve (enabling electric drive) before entering a zero-emission zone. Extensions to driver-aware scenario are realised using Markov chain based modelling of future power demand.

The paper is organized as follows: Section 2 describes the system model and theoretical results used in subsequent sections. Formulation and solution methods of the Model Predictive Control (MPC) based PHEV EM are presented in Section 3. These are followed by results of the implemented EM controller that are discussed in Section 4.

2. THEORY AND SYSTEM MODELING

MPC is employed to solve the predictive EM problem due its ability to track set-point trajectories in presence of

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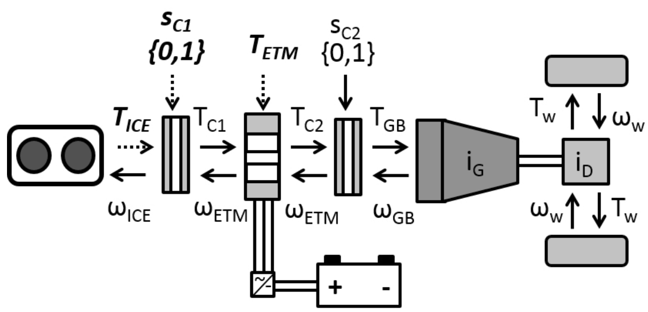

Fig. 1. Schematic of combustion engine assist powertrain

hard constraints on states and inputs. The investigations in this paper employ the Combustion Engine Assist (CEA) powertrain depicted in Fig. 1 as a use-case. CEA is a PHEV in parallel P2 topology with a downsized 2-cylinder ICE and an ETM (Beidl et al., 2012). The structure of the CEA powertrain is depicted in Fig. 1. The powerflow during propulsion is indicated by the torques (T) and speeds (ω) at the component interfaces. The controlled quantities namely, torque from ICE, ETM and ICE state are denoted by dotted lines. From the functional perspective, it is a full hybrid offering pure electric drive functionality by decoupling the combustion engine using the clutch C1.

2.1 Model Predictive Control

MPC realizes constrained finite horizon optimal control using control action resulting from repeated solution of an Optimal Control Problem (OCP) parameterized by the initial state. It uses a model which forecasts system behaviour over a time interval known as prediction horizon to determine control action for a certain control horizon. The generic nonlinear economic MPC for a prediction horizon of length N is of the form (Rawlings et al., 2012).

$$\min_u V_N(x,u) \tag{1}$$

$$\text{s. t. } x^+ = f(x,u) \qquad x(0) = x \qquad x(N)\,\epsilon\,\mathcal{X}_N$$
$$(x(k), u(k))\,\epsilon\,\mathcal{Z} \qquad k\,\epsilon\,\mathcal{Z}_{0:N-1}$$

V_N denotes the value function or cost function, $f(x,u)$ is the nonlinear system dynamics. $\mathcal{X}_N$ and $\mathcal{Z}$ denote the terminal set and feasbile set respectively. There exist three broad class of methods for solving OCP (Diehl et al., 2005). Dynamic Programming (DP) based on the principle of optimality solves the OCP by Hamilton-Jacobi-Bellman equation (HJB), a sufficient condition for optimality. Among others, the curse of dimensionality discourages its direct application. Variants of DP have been investigated specifically for EM-OCP (Wahl et al., 2014). Indirect methods uses the Pontryagins Minimum Principle to reduce the OCP to a two-point boundary value problem. Inequality constraints thereby lead to ODE with state dependent switches and hence are difficult to handle. Direct methods discretize the infinite dimensional OCP into finite dimensional NLP problem and solve it using well developed sparse structure exploiting solvers. Direct methods can handle inequality constraints better and shall be employed for solving the EM-OCP.

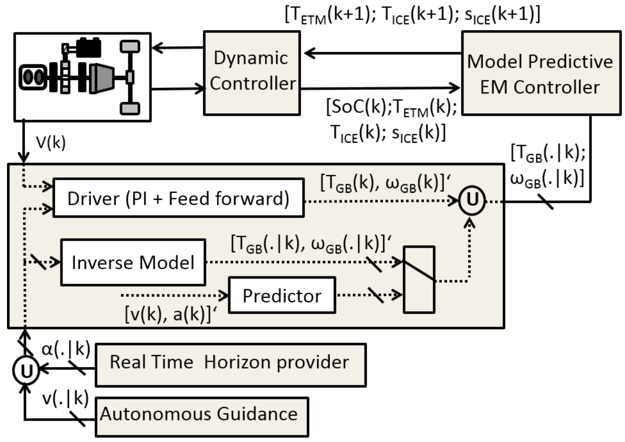

Fig. 2. MPC structure for PHEV EM

The structure of MPC employed for solving the EM-OCP is shown in Fig. 2. The slash symbol on the signals indicate that they are vector valued. The vector notation $x(.|k)$ stands for the predicted value for a horizon of length N based on the current value. $[x(k|k)x(k{+}1|k)...x(k{+}N|k)]^T$. The model predictive EM controller computes set point torque values of ETM and ICE as well as state of ICE from the predicted values of torque and speed at the gearbox input over the prediction horizon. The current value of state of charge(SoC), current state of ICE, torque values of ETM and ICE are fedback to the EM controller. The dynamic controller component of EM controller realises the command set point values (Vadamalu and Beidl, 2016). The torque and speed predictions $T_{GB}(.|k)$ and $\omega_{GB}(.|k)$ (GB stands for Gearbox) are computed from the driver model and an inverse model. The driver model is realised as two DoF controller with a feedforward part and a Proportional-Integral (PI) feedback controller. The feedforward part computes the torque and speed values based on set velocity, to the contrary the PI controller acts on the resulting small deviations. The inverse model is a non-causal representation of the vehicle longitundinal dynamics, computing torque and speed predictions from predicted vehicle velocity $v(.|k)$ and road grade vectors $\alpha(.|k)$ over the prediction horizon N. Information regarding future vehicle velocities and road grade with the current driver demand to generate speed and torque vectors at the gearbox input side with the length of the prediction horizon.

The MPC controller is consituted by the model used to represent the process, optimization algorithm, objective function and constraints. Model, cost function and constraints depend on problem formulation which is handled in Section 3. As discussed direct optimal control methods and hence Nonlinear programming (NLP), specifically quadratic programming (QP) solvers shall be used. Direct methods use a finite dimensional control trajectory parameterization but have different realizations to deal with state trajectories. This work uses a sequential approach, which solves the differential or discretized difference equation during optimization. Only the first element of the computed control vector is fed to the Dynamic Controller block, which realizes the set values using component-level controllers. The procedure is repeated the next sampling