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Bond Graph-Based Energy Balance Analysis of Forward and Backward Looking Models of Parallel Plug-In Hybrid Electric Vehicle

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Abstract

Design and optimization of a plug-in hybrid electric vehicle (PHEV) control strategy is typically based on a backward-looking (BWD) powertrain model, which ensures a high computational efficiency by neglecting the powertrain dynamics. However, the control strategy developed for BWD model may considerably underperform when applied to a forward-looking (FWD) powertrain model, which includes a dynamic driver model, powertrain dynamics, and corresponding low-level controls. This paper deals with bond-graph based modelling and energy balance analysis of BWD and FWD powertrain models for a P2 parallel PHEV-type city bus equipped with a 12-speed automated manual transmission. The powertrain consists of a motor/generator (M/G) machine supplied by the lithium-ion battery and placed at the transmission input shaft, and an internal combustion engine which can be disconnected from the rest of the powertrain by a main clutch placed between the engine and M/G machine. The BWD model is implemented in Matlab/Simulink environment whereas FWD model is developed in Simcenter Amesim. The BWD and FWD models are tested for different driving cycles reflecting different driving conditions. It is shown that the powertrain transient-related losses occurring during transmission gear shifting and engine switching predominantly contribute to the difference in energy consumption of the FWD model compared to the BWD model. It is also shown that, as the number of powertrain shifting and switching events is reduced by proper tuning of high-level control strategy, the difference between FWD- and BWD-model-related energy consumption becomes lower for the same driving cycle.

Introduction

The backward-looking (BWD) models, in which the powertrain dynamics are simplified through static relations, are commonly used for fuel and energy consumption predictions in hybrid electric vehicles (HEV) [1, 2]. These models rely on driving cycle data (vehicle velocity, acceleration and road grade time profiles) as inputs to determine the rest of the powertrain variables, such as engine and M/G machine torques and speeds, in a backward manner. Since the BWD model is computationally efficient, it is suitable for off-line or on-line optimizations of HEV power flow aimed at optimal coordination of multiple power sources. The BWD model is typically of first-order and describes only the slow battery state-of-charge (SoC) dynamics.

A forward-looking (FWD) model provides more precise mathematical description of the powertrain dynamics by using a set of state equations, it accounts for low-level control system dynamics, and describes the driver behavior [1, 3]. Since the FWD model is more faithful than the BWD model, it is used for more detailed analyses of powertrain dynamics behavior, synthesis and testing of low-level powertrain controls, comfort and drivability analysis, and verification of high-level control strategy [1].

HEV energy management strategies, such as those based on predetermined set of rules (i.e. Rule Based strategy, [4]), Pontryagin's Minimum Principle [5, 6], equivalent consumption minimization (ECMS, [7, 8]) or model predictive control (MPC, [9, 10]) are usually designed and preliminary verified by using BWD model, owing to its simplicity and computational efficiency. However, since the energy management strategies based on BWD model do not account for powertrain transient-related energy losses, they can underperform when applied on FWD models or vehicle. The modelling and analysis work presented in this paper represents a basis for development of a BWD-based, computationally efficient but more physically precise powertrain model, in Fig. 9 and Table 1. In the case t_{th} = 5 s, the FWD model predicts the energy consumption which is by 1.04 kWh higher than for the BWD model, while in the case t_{th} = 2s the energy consumption difference is increased to 1.269 kWh. Both FWD and BWD model have roughly similar aerodynamic drag energy losses E_{aero}, rolling resistance energy losses E_{roll}, gear efficiency losses $E_{tr,loss,g}$, and battery and M/G machine energy losses for the powertrain non-switching states $E_{batt,loss,s}$ and $E_{MG,loss,s}$, respectively. The major differences are present in the braking energy losses E_{brake}, battery, M/G machine and transmission energy losses in powertrain switching states $E_{batt,loss,t}$, $E_{MG,loss,t}$ and $E_{tr,loss,sl}$, respectively (see Fig. 10). These transient energy losses increase as the gear shift delay threshold t_{th} decreases, (cf. Fig. 10a and b), due to the the higher number of gear shifts N_g which cause more energy dissipation in the main clutch and synchronizers.

The observed difference in braking losses E_{brake} for the BWD and FWD models can be mainly attributed to the driver dynamics in FWD model since the driver sometimes demands a high braking power that can only be delivered by combination of mechanical brakes and the M/G machine. The main clutch contributes to the transmission slip-related losses $E_{tr,loss,sl}$ during engine-on events or gear shift events (if the engine is switched on), while the synchronizers contribute to these losses during each gear shift event. Finally, during switching states in hybrid mode, the engine is disconnected from the rest of the powertrain and the M/G machine is used to fill the engine torque hole in order to deliver the demanded wheel torque. This results in higher levels of M/G machine and battery powertrain transient-related energy losses, $E_{MG,loss,t}$ and $E_{batt,loss,t}$, respectively. In order to sustain SoC within acceptable levels, the high-level controller covers the aforementioned additional energy losses of the FWD model in CS mode by increasing the engine energy source (E_e) thus increasing the fuel consumption V_f.

Conclusions

The paper has presented a quasi-stationary/backward (BWD) and fully dynamic/forward (FWD) forms of powertrain model for a P2 parallel plug-in hybrid electric city bus with 12-speed automated transmission, including corresponding control strategies. The two models were simulated for a recorded city bus driving cycle, and the simulation results were used to conduct comparative energy balance analyses. The analysis has pointed out that the FWD model predicts around 20% higher fuel consumption when compared to the BWD one for comparable final SoC values. The energy loss differences between the two models increases as the number of gear shift and engine-on events increases. The BWD model achieves lower fuel consumption with more freedom to frequently shift gear ratios, while in the FWD model frequent gear shifts cause additional power losses in transmission, M/G machine and battery, and the fuel consumption grows.

Although the BWD model provides less accurate results than FWD model, its simulation execution time is substantially shorter making it more suitable for different optimization and large-sclae simulation studies. However, the high-level control strategy designed for BWD model may significantly underperform when applied to FWD model, which introduces the need for intermediate, computationally efficient and more precise powertrain model. The energy balance analysis presented in this paper would serve as basis for the development of such a model, which would account for powertrain transient energy losses, and which is the subject of our current research.

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Definitions/Abbreviations

BWD (model) - backward-looking model model
ECMS - equivalent consumption minimization strategy
FWD (model) - forward dynamical model
M/G (machine) - motor/generator machine
PI (controller) - proportional-integrtal controller
PHEV - plug-in hybrid electric vehicle
RB (controller) - rule-based controller