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Stochastic MPC for Optimal Energy Management Strategy of Hybrid Vehicle performing ACC with Stop&Go maneuvers

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Abstract: In urban zones, vehicles are often subject to multiple starts and stops, due mainly to different traffic conditions which are highly energy consuming. This paper investigates the problem of optimal energy management in a Plug-in Hybrid Electric Bus (PHEB) in urban environment for the purpose of energy consumption minimization. Hereby an original control architecture is proposed which comprises an Adaptive Cruise Control with Stop&Go (ACCwSG) control system and stochastic energy management strategy. To this end, first, an ACCwSG maneuvers has been developed with the aim of maintaining an inter-vehicular distance that ensures safety, as well as providing passenger comfort by generating smooth velocity profiles. Secondly, a Stochastic Model Predictive Control (SMPC) has been developed to optimize PHEB power split. Power demand is addressed as a Markov Decision Process (MDP). To prove the efficiency of the proposed strategy, it is compared with a deterministic rule based method. The obtained results demonstrate the reduction of the energy consumption in average around 13%. The present work is conducted on a dedicated high-fidelity dynamical model of the hybrid bus that was developed on MATLAB/TruckMaker software.

Keywords: Hybrid Electric Vehicle, ADAS (Advanced Driver-Assistance System), Energy Management, Adaptive Cruise Control, Stop&Go, Stochastic Control, MPC (Model Predictive Control), MDP (Markov Decision Process).

1. INTRODUCTION

Due to traffic congestion, traffic lights, a bus encounters frequent Stop&Go situations in urban environment. It results in increased fuel consumption, considerably, during the starts. Hybrid powertrain architecture of the studied bus makes profit of the deceleration phases, as a part of the energy can be recuperated to recharge the electric battery. From this point of view, the ACCwSG strategy brings the undeniable benefit. The acceleration and deceleration profiles optimization with an efficient energy management strategy can help to reduce the fuel consumption and respect the battery discharge rate.

Introduction of additional objectives to ACC, e.g., fuel economy and driver desired response has been investigated by some authors. Jonsson and Jansson (2004) proposed a Dynamic Programming based offline control method. It reduces the fuel consumption while allowing reliable tracking error (preceding car speed tracking). Usually in order to satisfy the fuel economy goal, one sacrifices the acceleration performance and the tracking capability. If an ACC system pursues good tracking capability only, it leads to unnecessary acceleration and emergency braking, which deteriorates the fuel economy of vehicle to some extent. A velocity control system in order to save the fuel consumption by involving traffic signal information was proposed by Yu et al. (2015). Model predictive control scheme was used in order to control the velocity predicting states of the vehicle and traffic signal switching. The algorithm judges whether a vehicle should accelerate or not when the vehicle cannot pass the traffic lights during the green phase. In the algorithm, the fuel economy was predicted using traffic signal information. A vehicle speed and vehicle-to-vehicle distance control algorithm for vehicle Stop&Go cruise control based on linear quadratic optimal control theory has been proposed in Yi et al. (2001). Kim (2012) formulated the optimization problem to find the optimal relative distance profile during a complete stop, and the optimal velocity profile during a starting motion. Linear quadratic optimal control theory has been used to develop the vehicle speed and distance control algorithm. A desired acceleration for the vehicle has been designed on the basis of the vehicle speed and distance control algorithm. It suggested that once leader car resumes the motion after a full stop, the host car is not obliged to follow the leader car, instead it can follow an optimal profile. The performance of ACC system should meet the safety and car-following requirements while providing slightly different level of driving comfort and fuel consumption, depending on the traffic situation and operating mode. Shakouri et al. (2015) investigated the application of three control approaches in ACC, the control structure was subdivided in two hierarchical loop, ACC with three different control strategies are implemented in the inner loop that are based on different approaches to simplify modeling of the vehicle dynamics. Three different nonlinear model-based approaches for the

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inner-loop controllers are investigated for this system: the conventional Proportional-Integral Gain Scheduling controller (PI+GS) and two other strategies based on the simplified modelling of the vehicle dynamics: Balance-Based Adaptive Controller (B-BAC) and Nonlinear Model Predictive Controller (NMPC).

Several energy management strategies have been suggested to manage the distribution of power between two sources Kamal et al. (2017) Ouddah et al. (2017) Abdrakhmanov and Adouane (2017a). Hemi et al. (2015) proposed a real time optimal control strategy based on Pontryagin's Minimum Principle (PMP), combined with a Markov chain approach for a fuel cell/supercapacitor electrical vehicle. A Markov chain model is added as a separate block for a prediction of required power. In recent years various stochastic model based predictive control (SMPC) algorithms have been proposed. A SMPC algorithm was developed by Ripaccioli et al. (2010) for power management, with the goal of optimizing the power splits in hybrid electric vehicle (HEV), while fulfilling bounds on the state of charge (SOC) of the battery and on the power availability. The power requested from the driver is represented by a Markov model. Instead of optimizing over driving cycle known a priori, the SMPC strategy optimizes over a distribution of future requested power demand, given the current one, at each sample time. Bichi et al. (2010) developed an approach based on SMPC used for improving the performance of powertrain control algorithms, by optimally controlling the complex system composed of driver and vehicle. The vehicle was modelled as a deterministic dynamical system, and the driver as a stochastic process, whose dynamics is updated online. Stochastic model predictive control is applied to optimize expected performance over a tree of scenarios, while enforcing constraints on states, inputs, and outputs. From a computational viewpoint, by assuming a linear system model they solve the SMPC problem via standard quadratic programming.

In this paper, we present an original control architecture that combines an Adaptive Cruise Control with Stop&Go (ACCwSG) maneuvers and a stochastic energy management strategy in order to control safely, precisely and with minimal energy consumption of studied PHEB. The proposed architecture uses an ACC controller supporting stop and go function. The main feature of this controller is to respect a desired vehicles inter-distance that ensures safety and passengers' comfort. Stochastic model predictive control optimizes PHEB power split among the available hybrid actuators according to a power demand profile. A Markov chain model has been proposed to predict future power demand. This proposed architecture gives a smooth speed profile while saving the fuel and the battery charge by giving the optimal power split between electric and hydraulic motors.

The rest of the paper is organized as follows. In section 2, the studied bus powertrain and its dynamical model are presented. Section 3, presents the detailed global control architecture description. In section 4, several simulation results are presented showing the efficiency of the proposed control strategy. Finally, conclusions and some prospects are given in the last section.

2. MODELING OF THE HYBRID BUS

The aim of this section is to illustrate the architecture and the mathematical model of the studied system, i.e., BUSINOVA hybrid bus, developed by SAFRA company. [1] This bus is composed of an electric motor, a hydraulic motor, an internal combustion engine and the battery as the propulsion powertrain system of the vehicle.

2.1 Hybrid bus powertrain architecture

The model of the studied hybrid bus is based on a series-parallel power-split hybrid architecture Bayindir et al. (2011). A simple block diagram of the power flows in the bus is shown in Fig. 1. The electric (EM) and hydraulic

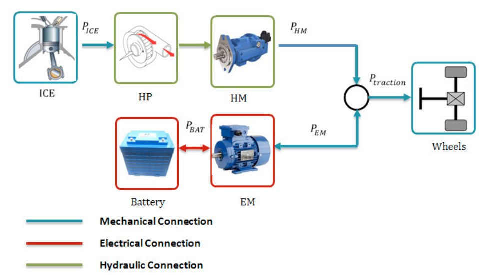

Fig. 1. Block diagram of the powertrain power flows. (ICE: internal combustion engine, HP: hydraulic pump, HM: Hydraulic motor, EM: electric motor)

(HM) motors are both directly connected to the transmission and can ensure simultaneously or independently the traction of the bus. On the other hand, the internal combustion engine (ICE) is coupled to a hydraulic pump (HP) for driving the HM, and therefore allowing the ICE load shifting.

The rotational speeds of the HM and the EM are imposed by the wheels speed in proportion to the reduction ratios of HM and EM respectively. Moreover, the rotational speed ω_{HM} and the torque T_{HM} are expressed as follows:

$$\begin{cases} \omega_{HM}\left(T_{ICE}, D_{HM}\right) = \frac{D_{HP} \cdot \eta_{v_{HM}} \cdot \omega_{ICE}}{D_{HM} \cdot \eta_{v_{HP}}} \\ T_{HM}\left(T_{ICE}, D_{HM}\right) = \frac{D_{HM} \cdot \eta_{m_{HM}} \cdot T_{ICE}}{D_{HP} \cdot \eta_{m_{HP}}} \end{cases} \quad (1)$$

where ω_{ICE}, T_{ICE} are respectively rotational speed and torque of the ICE, and D_{HM}, D_{HP}, $\eta_{m_{HM}}$, $\eta_{m_{HP}}$, $\eta_{v_{HM}}$, $\eta_{v_{HP}}$ are respectively displacement, mechanical efficiency and volumetric efficiency of the HM and the HP.

2.2 Dynamical model

This part is dedicated to the dynamical equations describing the bus. The purpose of the dynamical model is to have a realistic global behavior of the bus in order to validate the proposed energy management techniques. To describe it in a generic manner, assume that the bus is moving up with a slope of θ degree (cf. Fig. 2). The origin of the coordinates is situated in the Center of Mass (CoM). It is supposed that CoM of the bus is in its geometric center. The dynamical equation of the bus is given as follows:

$$\vec{F}_{tr} + \vec{F}_{rr} + \vec{F}_{ad} + \vec{F}_{g} + \vec{F}_{brake} = (M + M_{eq})\vec{a} \quad (2)$$

where $\vec{F}_{tr}$ is the traction force, $\vec{F}_{rr}$ the rolling resistance, $\vec{F}_{ad}$ the aerodynamic force, $\vec{F}_{g}$ the gravity force, $\vec{F}_{brake}$

[1] http://www.businova.com

the mechanical brake force, M the bus weight, M_{eq} the equivalent mass of rotating parts, $\vec{a}$ the bus acceleration. To produce the bus acceleration, it is necessary to take into

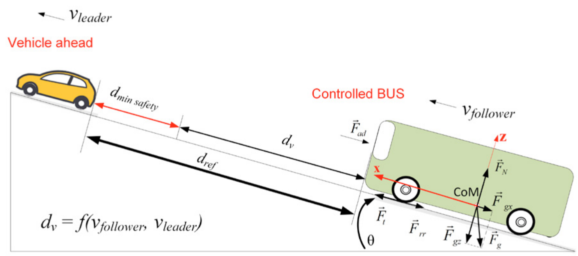

Fig. 2. Forces acting on the bus and ACCwSG scheme

account the moments of inertia of the rotating components (e.g., rotor of the EM, crankshaft of the ICE, driving axle, etc.). It is done by introducing the equivalent mass M_{eq} of the rotating components:

$$M_{eq} = \frac{i_g \eta_{pt} J_{rot}}{r^2} \tag{3}$$

where i_g is the gear ratio, η_{pt} the powertrain efficiency, J_{rot} the total inertia of the rotating components in the transmission, and r the wheel radius Cheng et al. (2007).

3. PROPOSED ACCwSG USING STOCHASTIC MPC ALGORITHM

3.1 Global Control Architecture

The proposed control architecture is presented in Fig. 3. It is composed of two principle blocks: ACCwSG and SMPC.

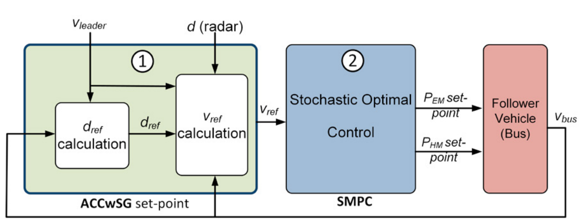

Fig. 3. Proposed global control architecture

The ACCwSG block ensures a safe distance between the bus and the ahead vehicle by generating smooth reference speed profile. The reference distance is a safe distance determined according to the current speed and distance between the vehicles, taking into account the acceleration/deceleration capabilities of the bus.

The SMPC block aims to generate the optimal power split to increase the fuel economy by taking into account uncertainties due to the bus weight, road slope, etc. translated through the requested power.

A detailed description of the ACCwSG and the SMPC algorithms are given in the sections 3.2 and 3.3, respectively.

3.2 Adaptive Cruise Control with Stop&Go algorithm

Block 1 in Fig. 3 corresponds to ACCwSG algorithm. Adaptive Cruise Control with Stop&Go (ACCwSG) is a mix of vehicle capability of maintaining a user-preset speed (Cruise Control), capability of keeping a safe distance from a preceding vehicle (ACC) and capability to perform maneuvers at low speeds (Stop&Go) (cf. Fig. 4) Abdrakhmanov and Adouane (2017b).

ACCwSG parameters proposed in this paper are presented in Fig. 2.

The aim of ACCwSG is to keep the inter-vehicular distance d_{ref} while vehicles are moving. At the full stop of both vehicles, the constant minimal safety distance $d_{min\ safety}$ must be respected.

In this paper, it is assumed that the current distance d between the vehicles is known and obtained by the bus sensors. In order to avoid collisions with the preceding car, the bus must follow the reference speed v_{ref} which must consider the following safety requirements. The reference distance d_{ref} to maintain between the vehicles is defined as follows:

$$d_{ref} = d_{min\ safety} + d_v \tag{4}$$

The distance $d_{min\ safety}$ is minimal distance to maintain at full stop of both vehicles. The distance d_v is defined as follows Zhang and Ioannou (2004):

$$d_v = T_h v + h^* v^2 \tag{5}$$

where $T_h = t_{dr} + t_{sensor} + t_{motor}$ a headway time which expresses the delays due to driver reaction, sensor perception, motors dynamics, respectively, $v = v_{follower}$ is the current bus speed.

The term h^* is calculated based mostly on the braking capability of the bus and the leader vehicle:

$$h^* = \frac{1}{2}\left(\frac{1}{a_{l_{max}}} - \frac{1}{a_{f_{max}}}\right) \tag{6}$$

with $a_{l_{max}}$ maximal deceleration of the leader, $a_{f_{max}}$ maximal deceleration of the bus. To ensure the passengers comfort and the safety, it is necessary that $a_{l_{max}} < a_{f_{max}}$ to take into account the extreme cases (e.g., preceding vehicles with emergency stop).

The calculation of d_{ref} is based on the parameters given in Table 1.

Table 1. Parameter values for d_{ref} calculation

Parameter	**Value**
Driver reaction time t_{dr}	0.4 s
Sensor perception delay t_{sensor}	0.1 s
Motors delay t_{motor}	0.1 s
Bus max deceleration $a_{f_{max}}$	-1.27 m/s^2
Leader max deceleration $a_{l_{max}}$	-6.87 m/s^2

The proposed ACCwSG system has the following switching logic (cf. Table 2):

- if $d \leq d_{ref}$: Starting from $d = d_{ref}$, it is considered that the vehicle is situated in the ACCwSG zone, and corresponding v_{ref} is thus applied.
- if $d > d_{ref}$: Both vehicles are at the safe distance from each other, so the bus becomes stable at the cruise speed v_{cc}.

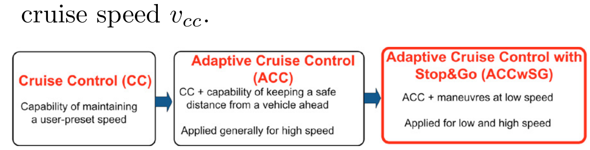

Fig. 4. ACCwSG concept

Condition	$d \leq d_{ref}$	$d > d_{ref}$
Reference Speed	v_{ref}	v_{cc}
Mode	ACCwSG	CC

Table 2. Switching logic between ACCwSG and CC

Two speed references proposed are in this paper, v_{cc} which is an external reference set by the driver, and the reference speed v_{ref} resulting from the ACCwSG system. In the ACCwSG mode, this reference depends mostly on the speed of the leader and the current inter-vehicular distance. The expression of v_{ref} is given as follows:

$$v_{ref} = v_{leader} + k_p(d - d_{ref}) - \dot{d}_{ref} \tag{7}$$

This expression contains the term d_{ref} (see equations (4) and (5)). After derivation, we obtain the following expression for the $\dot{d}_{ref}$:

$$\dot{d}_{ref} = T_h a + 2h^* va = (T_h + 2h^* v)a \tag{8}$$

with a bus acceleration and v bus speed.

To demonstrate the convergence of this control law, the Lyapunov theory has been used. The Lyapunov function candidate is defined as follows: $e = \frac{1}{2}(d - d_{ref})^2$. The time derivative of e:

$$\begin{aligned} \dot{e} &= (\dot{d} - \dot{d}_{ref})(d - d_{ref}) \\ &= (V_{leader} - V_{ref} - \dot{d}_{ref})(d - d_{ref}) \\ &= -k_p(d - d_{ref})(d - d_{ref}) \\ &= -k_p(d - d_{ref})^2 < 0 \end{aligned} \tag{9}$$

According to Lyapunov synthesis, this control is asymptotically stable and converges to 0 (while $d \neq d_{ref}$).

3.3 Stochastic Energy Management algorithm

The second part of the proposed control architecture consists of an optimal powersplit among the propulsion elements (cf. section 2.1). We consider the energy management problem of a series-parallel configuration of powertrain (cf. Fig. 1) where the electric motor (EM) is linked to hydraulic motor (HM) in parallel, meanwhile the HM power is supplied via the internal combustion engine (ICE) connected in series. The energy management strategy (block 2 in Fig. 3) is conceived in order to minimize the fuel consumption by optimally delivering the requested power. P_{req} is the total requested power that must be generated by the powertrain, the controller selects the P_{EM} which must be provided by the electric motor through the electric battery, and the P_{ICE} which must be provided by the HM through the ICE. The power balance equation for each sampling step k is given by equation (10):

$$P_{req}(k) = P_{EM}(k) + P_{ICE}(k) - P_{br}(k) \tag{10}$$

where P_{br} is the braking power by conventional friction brakes, in case where the braking kinetic energy can not be recovered or regenerative braking is not sufficient to provide the desired vehicle braking power. As the dynamics of the engine and the electric motor are much faster than the dynamics of the battery charge, the equation that connects the dynamics of the actuators with the one of the battery is:

$$SOC(k+1) = SOC(k) - KT_s P_{EM}(k) \tag{11}$$

with $SOC \in [0,1]$, $SOC = 1$ corresponds to a fully charged battery, T_s the sampling period, and $K > 0$ a positive constant identified for a generic HEV battery, it depends on the battery dynamics. Note that a positive value of P_{EM} indicates that power is provided by the battery to the motor, in the opposite case, the battery is charged by the motor (generator mode) on the regenerative braking phase.

The SMPC controls the variation of the engine power ΔP where

$$\Delta P(k) = P_{ICE}(k) - P_{ICE}(k-1) \tag{12}$$

Thus, we obtain the linear model from (10)-(12):

$$x(k+1) = Ax(k) + B_1 u(k) + B_2 w(k) \tag{13}$$

$$y(k) = Cx(k) + D_1 u(k) + D_2 w(k) \tag{14}$$

where

- $x(k) = \begin{bmatrix} SOC(k) \\ P_{ICE}(k-1) \end{bmatrix}$ the state vector,
- $u(k) = \begin{bmatrix} \Delta P(k) \\ P_{br}(k) \end{bmatrix}$ the control vector,
- $y(k) = P_{EM}(k)$ the output,
- $w(k) = P_{req}(k)$ is considered as a stochastic disturbance, which corresponds to the actions of the driver on the vehicle, where $w(k) \in W$. We suppose that at time k, the value w can be measured and we denote it by $w(k)$.
- $A = \begin{bmatrix} 1 & KT_s \\ 0 & 1 \end{bmatrix}$, $B_1 = \begin{bmatrix} KT_s & -KT_s \\ 1 & 0 \end{bmatrix}$, $B_2 = \begin{bmatrix} -KT_s \\ 0 \end{bmatrix}$
- $C = \begin{bmatrix} 0 & -1 \end{bmatrix}$, $D_1 = \begin{bmatrix} -1 & 1 \end{bmatrix}$, $D_2 = 1$

In order to design the SMPC controller, it is necessary to generate the stochastic perturbation using a Markov chain model.

The required power P_{req} is considered as a random process, denoted by w, and it is modeled as a Markov chain with the states $W = \{w_1, w_2, ..., w_s\}$, where obviously $w_i \in W$, for all $i \in \{1, ..., s\}$. The $Card(W) = s$ is chosen in such a way that it ensures a good compromise between the complexity of the stochastic model and its precision. The Markov Chain is defined by a transition probability matrix T such that:

$$[T]_{ij} = Pr[w(k+1) = w_j | w(k) = w_i] \tag{15}$$

where $i, j \in \{1, ..., s\}$, $w(k)$ the state of the Markov chain at time k, Pr is the probability distribution of $w(k+1)$. Using the Markov chain model with $w(k) = w_i$, the probability distribution of $w(k+l)$ is calculated as follows:

$$Pr[w(k+l) = w_j | w(k) = w_i] = [(T^l)' \cdot e_i]_j \tag{16}$$

where e_i is the i^{th} unitary vector, i.e., $[e]_i = 1$, $[e]_j = 0$ for all $j \neq i$.

To predict P_{req}, a Markov chain with $s = 300$ states is used. In this paper, the transition matrix T is initialized by $T = I$ (I Identity Matrix) and then updated online. We run the controller several times for different driving cycles, ECER15 (also known as UDC - Urban Driving Cycle), EUDC (European Urban Driving Cycle), ArtUrban (Urban Artemis), and NEDC (New European Driving Cycle), to learn the transition probabilities. The learning of the transition matrix is done through the power demanded by the driver P_{req} which translates the behavior of the driver and his way of driving. By counting the number of transitions of a power P_{reqi} to P_{reqj}, the number of occurrences for each transition from a state i to a state j is stored in $[n]_{ij}$.

The transition matrix T can be updated after each simulation, or when a large number of data is collected. To update the transition matrix, the following procedure has been used. For all $j \in \{1, 2, ..., s\}$

$$[T]_j = \frac{[n]_j + \lambda [T]_j}{\lambda + \sum_{k=1}^{s} [n]_{jk}} \quad (17)$$

Where λ the filtering parameter, $[T]_j$ the j^{th} row of transition matrix T, $[n]_j$ the j^{th} row of occurrence matrix $[n]$.

In the proposed paper, the SMPC algorithm presented in Bichi et al. (2010), Ripaccioli et al. (2010), is adopted in order to cope with the uncertainty on the requested power P_{req}. The proposed cost function with time depending references, is the new added element compared to the cited references, where the SOC is a time-invariant constant value. $P_{ICE_{ref}}(k)$ keeps the electric motor working with its maximum efficiency to respect the $SOC_{ref}(k)$, so as to maintain the battery charge above a certain threshold until the end of the day (cf. Fig. 5). This method allows a better usage of the electric energy and a better power management of the PHEB. The proposed approach based on SMPC is formulated according to the specific features of the PHEB models. The SMPC selects in this work the optimum engine power variation. It is presented in what follows the proposed SMPC formulation where the objective function (to be minimized) relies on an approximation of the expected value of:

$$J(k) = c_1 \Delta P(k)^2 + c_2 (P_{ICE}(k) - P_{ICE_{ref}}(k))^2 + c_3 (SOC(k) - SOC_{ref}(k))^2 \quad (18)$$

where $\Delta P(k)$ engine power variation (cf. equation (12)), P_{ICE} actual ICE power, $P_{ICE_{ref}}(k)$ is the ICE reference power, $SOC(k)$ actual SOC, $SOC_{ref}(k)$ is the reference SOC, and $c_i | i = 1,..3$ constant positive values, given the weight for each sub-criterion: c_1 enforces smooth mechanical power variations, c_2 leads the system to relieve the electric motor while using the ICE motor when the requested power exceeds electric motor nominal power, c_3 penalizes deviations from battery reference SOC_{ref} (cf. Fig. 5).

It is to be noted that $P_{ICE_{ref}}$ is defined to relieve the electric motor, in order to keep it in the nominal operating area P_n. For this reason, we proposed a switching logic (cf. Table 3).

Table 3. Switching logic for the ICE reference power

Condition	$P_{req} < P_n$	$P_{req} \geq P_n$
ICE reference power, $P_{ICE_{ref}}$	0	$P_{req} - P_n$

The reference SOC_{ref} is time-variable. The BUSINOVA bus is a plug-in hybrid electric vehicle and its standard functioning time is n hours a day (so called "course of a day"). Fig. 5 illustrates an example of a reference SOC baseline for a course of a day corresponding to 8h. By the end of a day, the bus has to reach its SOC_{min} value and can be recharged during all the night long to ensure the service the next day. In this work, the principle idea is to consider that a better usage of the electric energy is such that it is available until the end of the day (during for instance 8 hour operational cycle), and this is considered as an ideal functioning of the bus. The working hypothesis behind this assumption is to use the maximum amount of energy that can be consumed from the battery in one day driving so that the battery energy is spread as uniformly as possible in one working day. This implies the smooth battery discharging rate (C-rate), avoidance of the high or

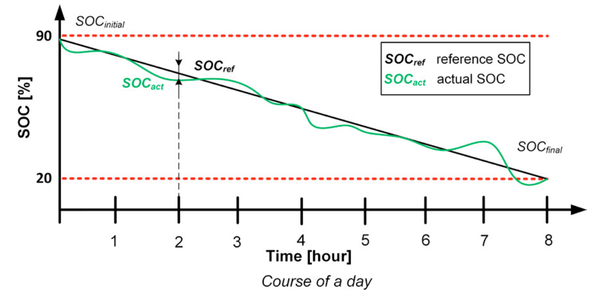

Fig. 5. Reference SOC baseline

low SOC and excessive depth of discharge, which lead to a high rate of battery capacity loss Tang et al. (2015) . As Li-ion batteries represent a big part of a hybrid electric vehicle cost, the clear interest is to prolong the battery life. Based on this hypothesis, the SOC_{ref} is updated each ΔT in order to guide the energy management strategy solutions produced by the proposed SMPC.

In order to guarantee a prolonged battery life and to respect electro-mechanical limitations, the state, manipulated inputs and outputs are subject to the constraints:

$$\mathbf{X} = \{x \in R^2, \begin{bmatrix} SOC_{min} \\ 0 \end{bmatrix} < x < \begin{bmatrix} SOC_{max} \\ P_{ICEmax} \end{bmatrix}\}$$

$$\mathbf{U} = \{u \in R^2, \begin{bmatrix} -\Delta P_{min} \\ 0 \end{bmatrix} < u < \begin{bmatrix} \Delta P_{max} \\ P_{brmax} \end{bmatrix}\}$$

$$\mathbf{Y} = \{y \in R, P_{EMmin} < y < P_{EMmax}\}$$

4. SIMULATION RESULTS

Below the simulation results for the proposed global control architecture are presented. The SMPC supporting ACCwSG function has been tested for several standardized urban driving cycles Barlow et al. (2009) to validate its performance. A driving cycle determines the leader vehicle speed profile. Initial distance between two vehicles is $d_{min\ \ safety} = 5$ m (cf. Fig. 2). The bus driver aims to drive at preset velocity $v_{cc} = 40$ km/h.

The initial conditions are $SOC(0) = 0.9$, $P_{req}(0) = 0$, $\Delta P_{max} = \Delta P_{min} = 1kW$ and $P_n = 10kW$. The cost function in equation (18) is normalized and the weight coefficients are chosen so that $\sum_{i=1}^{3} c_i = 1$. For the simulations presented below, the following weight coefficients were chosen: $c_1 = 0.4$, $c_2 = 0.4$ and $c_3 = 0.2$.

In order to validate the proposed control strategy four standard urban driving cycles were chosen: ECER15, EUDC, ArtUrban, and NEDC. The simulation results are summarized in Table 4. In order to estimate the efficiency of the proposed SMPC energy management strategy (EMS), it is compared with the results obtained applying a Rule-Based (RB) EMS Hofman et al. (2007). The columns **Diff** in Table 4 corresponds to the percentage of improvement of the SMPC compared to RB EMS. "+" corresponds to a positive improvement, "-" means that RB EMS demonstrated better performance.

Globally, the SMPC outperforms RB EMS in average by 12.98% from the consumed energy point of view. The consumed energy E_{cons} given by the column **Energy [kWh]** in Table 4 is calculated as follows:

Table 4. Comparison of the Rule Based strategy and SMPC strategy

Driving Cycle	Duration $[s]$	ΔSOC [%]			Fuel $[l]$			Energy $[kWh]$		**Energy Diff. [%]**
		RB	SMPC	**Diff. [%]**	RB	SMPC	**Diff. [%]**	RB	SMPC	
ECER15	389	1.642	1.002	**+38.97**	0.045	0.064	**-42.22**	1.208	1.098	**+10.01**
EUDC	398	2.424	1.779	**+26.61**	0.010	0.022	**-54.50**	1.234	1.053	**+14.66**
ArtUrban	1985	6.376	2.889	**+54.68**	0.264	0.399	**-51.13**	5.575	5.131	**+7.96**
NEDC	2359	7.092	5.987	**+15.58**	0.116	0.072	**+38.00**	4.457	3.597	**+19.29**
Average	-	-	-	**+33.96**	-	-	**-27.46**	-	-	**+12.98**

$$E_{cons} = \int_0^{t_f} P_{EM} dt + \int_0^{t_f} Q_{LHV} \dot{m}_f dt \qquad (19)$$

where P_{EM} is the electric motor consumed power, $\dot{m}_f$ fuel consumption rate, and $Q_{LHV} = 43MJ/kg$ lower heat value for diesel.

To illustrate the performance graphics NEDC standard driving cycle (SDC) was chosen. In Fig. 6-9 the simulation results are presented. Fig. 6 presents the bus ACCwSG performance results. The driving cycle lasts 2360 s. The upper figure shows the speed profiles. One can see that the bus follows smooth speed profile, ensuring a safe distance between two vehicles (see lower figure). Starting from ≈1060 s and ≈2240 s the bus stops following the leader vehicle and maintains the preset cruise speed.

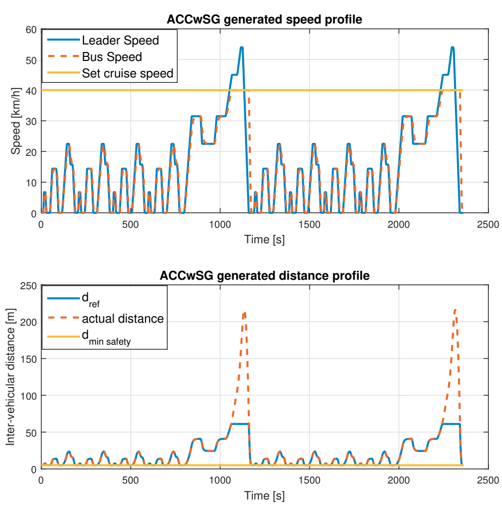

Fig. 6. Speed and Distance Profiles for NEDC SDC

Fig. 7 presents the Powersplit profile for both EMS. Although the total power demand is the same, the powersplit influences the electric energy and fuel consumption of the bus.

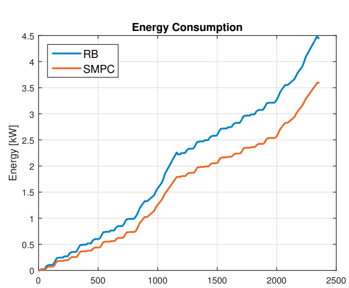

Fig. 9. Energy Profile for NEDC SDC

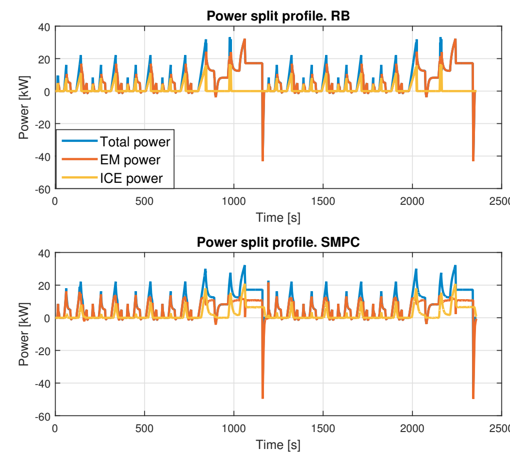

Fig. 7. Powersplit Profile for NEDC SDC

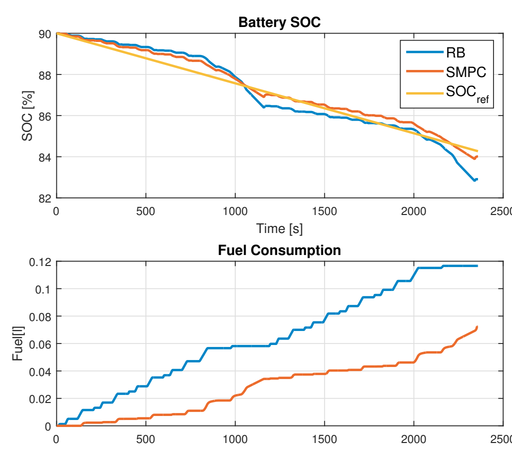

Fig. 8. SOC and fuel consumption comparison for NEDC SDC

Fig. 8 presents the battery SOC and fuel consumption graphs. One can see that the SMPC distributes power in such a way that the battery SOC converges to the referenced SOC_{ref}, as opposed to RB EMS, where the battery final SOC is lower than the SOC_{ref}. The rest of the power is supplied by the ICE. Fig. 8 shows that the SMPC consume less fuel as well for the given cycle. To illustrate a global energetic performance, we make use of equation (19). Fig. 9 proves that from the energy point of view, the SMPC EMS provides less consumption (notably, 4.457 kWh vs 3.597 kWh, thus 19.29% of improvement).

5. CONCLUSION AND PROSPECTS

This paper presented a global control architecture, including an ACCwSG and energy management strategy based on SMPC for energy optimization of a HEV. The developed overall architecture finds a highly practical application for the studied heavy urban hybrid bus, which is always subject to frequent starts and stops phases (phases which are generally subject to important energy consumption).

First, the ACCwSG algorithm has been proposed. It ensures a safe distance from the preceding car, taking into account the deceleration capabilities of the bus and anticipating an abrupt deceleration by the leader vehicle. Furthermore, the proposed ACCwSG generates smooth reference speed profile enabling the passengers comfort. Afterwards, the energy management strategy based on a Stochastic MPC has been designed to decrease the energy consumption of the bus. The required power is considered as a random Markov process, encompassing uncertainties with regards to the road profile, bus weight, etc. The proposed strategy has been tested and validated for several standard driving cycles and has demonstrated its efficiency compared to rule-based methods where an average of improvement about 13% has been observed.

It is planned in near future to implement and validate the proposed energy management strategy on the real studied bus.

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REFERENCES

Abdrakhmanov, R. and Adouane, L. (2017a). Dynamic programming resolution and database knowledge for online predictive energy management of hybrid vehicles. In International Conference on Informatics in Control, Automation and Robotics (ICINCO). Madrid-Spain.

Abdrakhmanov, R. and Adouane, L. (2017b). Efficient acc with stop&go maneuvers for hybrid vehicle with online sub-optimal energy management. In IEEE 11th International Workshop on Robot Motion and Control (RoMoCo). Wasowo-Poland.

Barlow, T.J., Latham, S., McCrae, I., and Boulter, P. (2009). A reference book of driving cycles for use in the measurement of road vehicle emissions. TRL Published Project Report.

Bayindir, K.Ç., Gözüküçük, M.A., and Teke, A. (2011). A comprehensive overview of hybrid electric vehicle: Powertrain configurations, powertrain control techniques and electronic control units. Energy Conversion and Management, 52(2), 1305–1313.

Bichi, M., Ripaccioli, G., Di Cairano, S., Bernardini, D., Bemporad, A., and Kolmanovsky, I.V. (2010). Stochastic model predictive control with driver behavior learning for improved powertrain control. In Decision and Control (CDC), 2010 49th IEEE Conference on, 6077–6082. Atlanta, USA.

Cheng, Y., Lataire, P., et al. (2007). Research and test platform for hybrid electric vehicle with the super capacitor based energy storage. In Power Electronics and Applications, 2007 European Conference on, 1–10. Aalborg, Denmark.

Hemi, H., Ghouili, J., and Cheriti, A. (2015). Combination of markov chain and optimal control solved by pontryagins minimum principle for a fuel cell/supercapacitor vehicle. Energy Conversion and Management, 91, 387–393.

Hofman, T., Steinbuch, M., Van Druten, R., and Serrarens, A. (2007). Rule-based energy management strategies for hybrid vehicles. International Journal of Electric and Hybrid Vehicles, 1(1), 71–94.

Jonsson, J. and Jansson, Z. (2004). Fuel optimized predictive following in low speed conditions. IFAC Proceedings Volumes, 37(22).

Kamal, E., Adouane, L., Abdrakhmanov, R., and Ouddah, N. (2017). Hierarchical and adaptive neuro-fuzzy control for intelligent energy management in hybrid electric vehicles. In IFAC World Congress. Toulouse-France.

Kim, S. (2012). Design of the Adaptive Cruise Control Systems: An Optimal Control Approach. PhD thesis, University of California, Berkeley.

Ouddah, N., Adouane, L., Abdrakhmanov, R., and Kamal, E. (2017). Optimal energy management strategy of plug-in hybrid electric bus in urban conditions. In International Conference on Informatics in Control, Automation and Robotics (ICINCO). Madrid-Spain.

Ripaccioli, G., Bernardini, D., Di Cairano, S., Bemporad, A., and Kolmanovsky, I. (2010). A stochastic model predictive control approach for series hybrid electric vehicle power management. In American Control Conference (ACC), 2010, 5844–5849. IEEE.

Shakouri, P., Czeczot, J., and Ordys, A. (2015). Simulation validation of three nonlinear model-based controllers in the adaptive cruise control system. Journal of Intelligent & Robotic Systems, 80(2), 207–229.

Tang, L., Rizzoni, G., and Onori, S. (2015). Energy management strategy for hevs including battery life optimization. IEEE Transactions on Transportation Electrification, 1(3), 211–222.

Yi, K., Hong, J., and Kwon, Y. (2001). A vehicle control algorithm for stop-and-go cruise control. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 215(10), 1099–1115.

Yu, K., Yang, J., and Yamaguchi, D. (2015). Model predictive control for hybrid vehicle ecological driving using traffic signal and road slope information. Control theory and technology, 13(1), 17–28.

Zhang, J. and Ioannou, P. (2004). Integrated roadway/adaptive cruise control system: Safety, performance, environmental and near term deployment considerations. California Partners for Advanced Transit and Highways (PATH).