On-Line Energy Management Strategy For Hybrid Electric Vehicles Based On AMPC

Jun Ma[1], A. F. M. Shahen Shah[2], Mustafa Baysal[3], Haci Ilhan[4]
[1,3]Department of Electrical Engineering, [2,4]Department of Electronics and Communication Engineering
Yildiz Technical University, Istanbul, Turkey.
junmayusuf@gmail.com[1], shahen.shah@hotmail.com[2], baysal@yildiz.edu.tr[3], ilhanh@yildiz.edu.tr[4]

Abstract

In this paper, Adaptive Model Predictive Control (AMPC) based Energy Management Strategy (EMS) for Hybrid Electric Vehicles (HEVs) is proposed to minimize the hydrogen consumption and to increase the energy sources lifetime. The EMS problem is simplified according to the control structure of the vehicle. Moreover, adaptive algorithm is used to dynamically adjust the weights of targets. The Energetic Macroscopic Representation (EMR) and control scheme of the vehicle is implemented in MATLAB-Simulink^{TM}. To test the performance two standard driving cycles and a real urban cycle are used. The simulation results of proposed AMPC show a noticeable improvement in fuel economy and battery charge-sustainability.

1. Introduction

As the energy is increasingly depleted and environmental pollution becomes a serious concern, HEVs attract more and more attention for their advantages of energy saving and environmental protection [1]. The current hybrid car generally refers to the internal combustion engine, generator, and energy storage system (battery or ultracapacitor). Since HEVs take into account the advantages of traditional fuel vehicles and pure electric vehicles, they can be designed to achieve different goals such as emission reduction and fuel economy [2]. However, its structure is much more complex than traditional cars and pure electric vehicles because of more connected components, which makes the design of energy management strategy also more complex. The excellent EMS is the key to the energy saving of hybrid electric vehicles [3]. Therefore, the EMS of HEVs has become one of the hot topics for experts and scholars in recent years.

Due to the nonlinearity, dynamic and constrained characteristics of the model, energy management optimization problem has been a nonlinear and dynamic optimization problem as applied to control system [4]. In the past years, lots of optimization approaches were proposed for offline and online EMS problem. Dynamic Programming (DP) algorithm has been used for energy management of HEV since 2000 and is recognized as an ideal hybrid energy management method, which can achieve global optimization and a better improvement in the fuel economy [2,5]. But this method requires the driving cycle and thus computationally demanding in advance, so it is suitable to be used in offline optimization [3]. It can also be used as benchmarks to evaluate other online optimization approaches. Although Stochastic Dynamic Programming (SDP) algorithm is proposed to reduce the computation burden, it still could not be applied in real-time driving cycles [6]. In order to solve computation problem, instantaneous optimization methods were proposed, namely Equivalent Consumption Minimization Strategy (ECMS). The basic idea of ECMS is to transfer energy cost of battery to fuel consumption by defining Equivalent Factor (EF). Sciarretta A et al. [7] adopted ECMS from the perspective of real-time EMS and used different EFs to optimize the solution considering the difference between the charging and discharging process. Musardo C et al. [8] proposed adaptive ECMS which can estimate the EF according to the historical and current driving conditions. Although this method has good performances on each short interval and can be used in real time, it may not give best decisions for whole driving cycle because the dynamic characteristic of model is not considered. Model Predictive Control (MPC), which can solve EMS optimization problem over a finite driving interval rather than at each instant time, is a better choice as a compromise between the computational cost and the non-causality of a globally optimal DP solution and also the faster, causal, but instantaneous ECMS solution [4]. H. Ali Borhan et al. [9] proposed LTV-MPC method to determine the given power ratio between engine and battery, by linearizing the nonlinear and constrained optimal control problem and defining the cost function included fuel consumption and State-of-Charge of battery but not taking battery recharge cost into account. Umberto Sartori et al. [10] also used the Nonlinear MPC method and considered the battery recharge equivalent cost but ignored the charge-sustainability of battery. Both of later two studies took the demanded torque and speed as the control input, which increases the complexity of the optimization problem and results in huge computational cost.

In this paper, an AMPC based EMS for Fuel Cell Hybrid Electric Vehicle (FCHEV) is proposed to decrease the hydrogen consumption and to extend the lifetime of system. Firstly, the energy management optimization problem is simplified according to the control structure deduced by EMR. Secondly, the quadratic cost function considering hydrogen consumption, battery recharge equivalent cost and battery charge-sustainability is built to estimate the performance of FCHEV. Then adaptive algorithm is also used to dynamically adjust the weights of targets. Finally, simulation results of diverse driving cycles are evaluated to exhibit the efficiency of the proposed adaptive MPC compared to the conventional ECMS method.

The rest of the paper is arranged as follows. Section 2 presents the system configuration and vehicle models. An online EMS based on AMPC for parallel hybrid electric vehicle is proposed in section 3. Section 4 presents the simulation results. Section 5 concludes the paper.

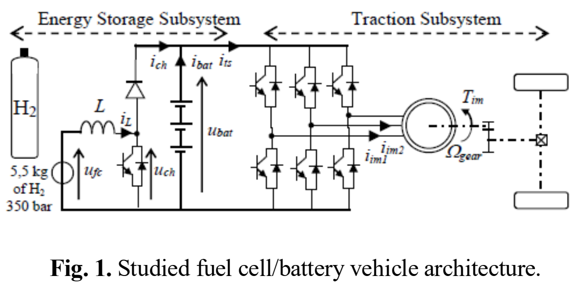

Fig. 1. Studied fuel cell/battery vehicle architecture.

2. Fuel cell/battery vehicle

2.1 System configuration

The studied fuel cell/battery vehicle architecture taken from the IEEE VTS Motor Vehicles Challenge 2017 is as shown in Fig. 1[11]. It is consisted with energy storage subsystem and traction subsystem which are connected by a voltage-source-inverter. A compressor ensures the supply of oxygen for FC and it is considered as a voltage source using its static polarization curve [11]. A non-reversible boost chopper and a smoothing inductor connected FC with the energy storage sub-system. Seen from the Fig.1 the energy storage subsystem directly connected to traction sub-system can reduce the number of converters and the complexity of system, this also improves the energy economy. The studied vehicle parameters are presented in Table 1.

Table 1. Fuel cell/battery vehicle parameters

Fuel cell	system	PEMFC
	voltage	40-60 V
	Rated power	16 kW
	maximum current	400A
H2	5.5kg 350bar	
Smoothing inductors	5.5 mΩ, 0.25 mH	
Lithium Iron Phosphate (LiFePO4) battery	80 V, 40 Ah	
Electric drive	15 kW	
Vehicle mass	698 kg	
maximum speed	85 km/h	

2.2 Modelling

2.2.1 Fuel Cell

Fuel Cell system (FC) is consisted of the fuel cell, a smoothing inductor, a boost chopper and other ancillaries which is not modeled in this paper. In [11], the fuel cell having an experimentally validated quasi-static model is used as a voltage source, H_2 mass flow $\dot{r}$ is also considered as a static characteristic expressed in (1). For the parallel architecture of fuel cell and battery, power split rate is as same as demanded current split rate.

$$\dot{r} \qquad + h_2 \tag{1}$$

where g_2 , h_2 are the constants obtained from experiments [11].

2.2.2 Battery

Different from the SoC of the battery (SoC_{bat}) formulated in [1, 4, 10], in the challenge SoC_{bat} is estimated as following[11]:

$$SoC_{bat} = SoC_{init} - \int \frac{100 i_{bat}}{3600 Q_{bat}} dt \tag{2}$$

where SoC_{init} is the initial SoC of the battery, Q_{bat} is the battery capacity and i_{bat} is the battery current.

According to the Kirchhoff's current law, the relationship of the energy storage subsystem and traction subsystem is as following:

$$i_{bat} = i_{ts} - i_{hfc} \tag{3}$$

$$i_{hfc} = m_{hfc} \eta_{hfc}^{k} i_{fc}, k = \begin{cases} 1, \text{if } \ P > 0 \\ -1, \text{if } \ P < 0 \end{cases} \tag{4}$$

where m_{hfc} is the modulation ratio of the FC chopper; $\eta_{hfc} = 95\%$ is the average efficiency of the chopper [11].

The details about other parts of system can find in [11] and the control system structure is shown in Fig. 2 [11].

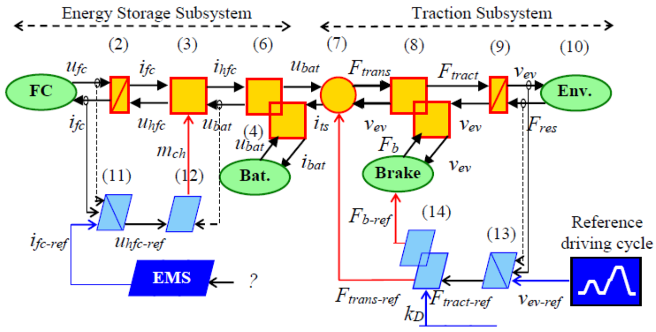

Fig. 2. EMR and inversion-based control of the studied fuel cell vehicle

3. Proposed Energy Management Strategy

3.1 Problem Statement

Hybrid Electric Vehicles have better performance on fuel economy compared to traditional single power supplement vehicles due to combined advantages of fuel cell and battery. The power distribution between fuel cell and battery directly influences the proficiency of whole system. According to the model presented in section II, EMS element will determine the distribution of power demand from driver by giving reference current for fuel cell control system under the certain constraints, in other word, power split problem will be transferred to a current split optimal problem due to the model used in this paper. In order to focus on the EMS, the breaking strategy will not be considered in this paper.

Based on the vehicle model in this paper, the energy storage system can be simplified as

$$\begin{cases} i_{bat}(\mathrm{t}) = i_{ts}(t) - \mathrm{m}_{hfc} i_{fc}(t) \eta_{hfc} \\ \dot{So(} \qquad)0 i_{bat}(t) / (3600 Q_{bat}) \end{cases} \tag{5}$$

where $\dot{So(}$ is the energy consumption rate of battery, η_{hfc} takes the value 0.95 because in this paper when current demand i_{ts} less than 0, the fuel cell system will work at the minimum power point. According to the introduction part, a quadratic cost function taking three targets into account is given to minimize fuel consumption and AMPC method is proposed to solve it as followed.

$$J = \int_{t}^{t+\Delta t} (\omega_f \bullet (\dot{r} \qquad \omega_{ef} \bullet (\dot{So(} \qquad \omega_{SoC_{bat}} \bullet (SoC_{bat}(\tau) - SoC_r)^2) d\tau \tag{6}$$

where Δt is the prediction horizon, ω_f , ω_{ef} , $\omega_{SoC_{bat}}$ are penalty weights of fuel consumption, equivalent factor of battery energy consumption and deviation of SoC_{bat} from the ideal value SoC_r respectively. Therefore, the moving horizon optimal problem in each interval is defined by

$$\begin{gathered} \min_{\{i_{fc}(t), i_{bat}(t)\}} J = \int_{t}^{t+\Delta t} (\omega_f \bullet (\dot{r} \qquad \omega_{ef} \bullet (\dot{So(} \\ \omega_{SoC_{bat}} \bullet (SoC_{bat}(\tau) - SoC_r)^2) d\tau \end{gathered} \tag{7}$$

$$\begin{cases} SoC_{bat.\min} \le SoC_{bat}(t) \le SoC_{bat.\max} \\ 0 \le i_{fc}(t) \le i_{fc.\max} \\ \Delta i_{fc.\min} \le \Delta i_{fc}(t) \le \Delta i_{fc.\max} \end{cases}$$

where $\Delta i_{fc.\min}$, $\Delta i_{fc.\max}$ represent the limitation of fuel cell current generation which reduce stack faults and degradation [11].

3.2 MPC model

MPC optimization problem can be transferred to quadratic program (QP) with linear inequality constraints, the standard format is:

$$\Delta U^* = arg\,\min_{\Delta U} \Delta U^T H \Delta U + 2\Delta U^T f$$

Subject to

$$A\Delta U \le b \tag{8}$$

where H, f are the constant matrix; A is constraint coefficient matrix; b is the column vector; ΔU^* is the optimal input sequence. The optimal control input sequence is

$$u(k) = u(k-1) + \Delta u(k) \tag{9}$$

First the optimization problem and energy storage system state equation can be formulated in discrete-time as

$$\begin{aligned} &min\ \omega_f \sum_{k=0}^{p-1} i \qquad \omega_{ef} \sum_{k=0}^{p} \Delta SoC_{bat}(k)^2 \\ &+\omega_{SoC_{bat}} \sum_{k=1}^{p} (SoC_{bat}(k) - SoC_r)^2 \\ &s.t. \\ &\begin{cases} SoC_{bat.\min} \le SoC_{bat}(k) \le SoC_{bat.\max}, & k = 1, \cdots, p \\ 0 \le i_{fc}(k) \le i_{fc.\max}, & k = 0, 1, \cdots, p\text{-}1 \\ \Delta i_{fc.\min} \le \Delta i_{fc}(k) \le \Delta i_{fc.\max}, & k = 0, 1, \cdots, p\text{-}1 \end{cases} \end{aligned} \tag{10}$$

$$\begin{cases} I_{fc} = I_{fc0} + M\Delta I_{fc} \\ I_{bat} = I_{ts} - m_{hfc}\eta_{hfc} I_{fc} \\ Y = Y_0 + \sigma M(m_{hfc}\eta_{hfc} I_{fc} - I_{ts}) / (360 Q_{bat}) \end{cases} \tag{11}$$

where p is the step of prediction horizon; σ is the interval of each prediction step; M is the lower triangular matrix;

$I_{fc0} = \left[i_{fc}(-1) \cdots \right.$ $\quad Y_0 = \left[SoC_{bat}(0) \cdots \quad (0) \right]^T$

where $i_{fc}(-1)$ is the measured fuel cell current at the moment of optimization) are the initial value of fuel cell current and SoC_{bat} sampled in every MPC optimization cycle respectively; $I_{bat} = \left[i_{bat}(0)\ i_{bat}(1) \cdots \quad) \right]^T$ is the battery current sequence; $I_{ts} = \left[i_{ts}(0)\ i_{ts}(1) \cdots \right.$ ^{T} is the input current demand from driver; $Y = \left[SoC(1) \cdots \quad p) \right]^T$ is the SoC_{bat} sequence.

The equation (11) can be rewritten in matrix and then comparing with equation (8), the coefficients of QP problem, H and f can be obtained as followed. It is easy to find A and b by using same method.

$$\begin{cases} H = \omega_{SoC_{bat}} \left(\dfrac{m_{hfc}\eta_{hfc}}{360 Q_{bat}} \right)^2 M^T M^T M M + \left[\omega_{ef} \left(\dfrac{m_{hfc}\eta_{hfc}}{360 Q_{bat}} \right)^2 + \omega_f {g_2}^2 \right] M^T M \\ f = \omega_f g_2 M^T (g_2 I_{fc0} + B) + \omega_{ef} \dfrac{m_{hfc}\eta_{hfc}}{(360 Q_{bat})^2} M^T (m_{hfc}\eta_{hfc} I_{fc0} - I_{ts}) \\ +\omega_{SoC_{bat}} \begin{bmatrix} \dfrac{m_{hfc}\eta_{hfc}}{360 Q_{bat}} M^T M^T (Y_0 - L) \\ + \dfrac{m_{hfc}\eta_{hfc}}{(360 Q_{bat})^2} M^T M^T M (m_{hfc}\eta_{hfc} I_{fc0} - I_{ts}) \end{bmatrix} \\ A = [M; -M; I; -I; -M^2; M^2] \\ b = [C_1 - I_{fc0}; I_{fc0}; C_2; C_2; \dfrac{360 Q_{bat}}{m_{hfc}\eta_{hfc}} (Y_0 - C_4) - \dfrac{MR}{m_{hfc}\eta_{hfc}} + M I_{fc0}; \\ \dfrac{360 Q_{bat}}{m_{hfc}\eta_{hfc}} (C_5 - Y_0) + \dfrac{MR}{m_{hfc}\eta_{hfc}} - M I_{fc0}] \end{cases} \tag{12}$$

where B, L and are constant matrixes representing h_2, SoC_r; C_1, C_2, C_3, C_4, C_5 are constraints matrixes; I is identity matrix.

3.3 AMPC based Energy Management Strategy

The on-line energy management optimization problem presented in this paper is formulated as a repeated solution of a finite horizon optimal control problem considering system dynamics, input and state constraints [13]. In the proposed AMPC method, the penalty weight $\omega_{SoC_{bat}}$ will be adjusted according to the deviation of SoC_{bat} which shows the system dynamics. Then the formulated MPC model is applied to obtain the control inputs with measured data of system at each sampling time. Moreover, the stability and disturbance rejection properties of MPC were tested in [14]. The specific actions of the AMPC based EMS are performed at each sampling time as followed.

- Measurement of the system state (SoC_{bat},fuel cell current i_{fc}, current demand i_{ts},the chopper modulation ratio m_{hfc})
- Adjustment of the $\omega_{SoC_{bat}}$ with PI controller (13) according to the deviation of SoC_{bat}

$$\begin{aligned} \omega_{SoC_{bat}}(t) &= \omega_0 + K_p \left| SoC_{bat}(t) - SoC_r \right| \\ &+ K_i \int_{t0}^{t} (SoC_{bat}(\tau) - SoC_r) d\tau \end{aligned} \tag{13}$$

- Prediction of the current demand over the prediction horizon and preparation of the coefficient H, f
- Application of the current split strategy AMPC obtaining the optimal control input for the first timeslot.

In order to estimate current demand in the future correctly, the changing rate of current demand γ is computed analytically as following (14) via various simulations and observations and the simulation performance is in Fig.3. Then the i_{ts} in the perdition horizon is calculated as (15).

$$\gamma=\begin{cases}\Delta i_{ts}, & if\ 0\le|\Delta i_{ts}|\le 2\\ 0.5\Delta i_{ts}, & if\ 2<|\Delta i_{ts}|\le 4\\ 0.1\Delta i_{ts}, & if\ 4<|\Delta i_{ts}|\le 6\\ -0.1\Delta i_{ts}, & if\ 6<|\Delta i_{ts}|\le 8\\ -0.5\Delta i_{ts}, & if\ 8<|\Delta i_{ts}|\end{cases} \quad (14)$$

$$i_{ts}(k)=i_{ts}(k-1)+\gamma,\ \ k=0,1\cdots \quad (15)$$

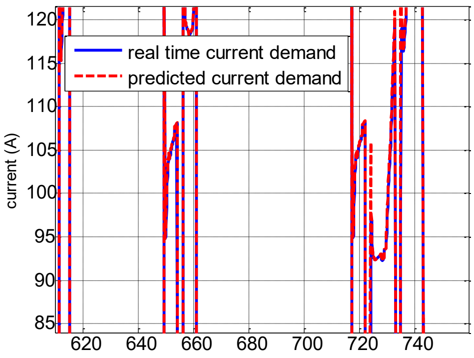

Fig. 3. Comparison of predicted and real-time current demand

In this method, although $\omega_{SoC_{bat}}$ is adjusted by equation (13), based on the rule-based control some principles are also set to limit it such as increasing the penalty weight $\omega_{SoC_{bat}}$ to huge value when it is less than safe range 0.5, due to the extreme situations which can result in over discharge of battery.

4. Simulation Results

In this paper, considering the robustness and availability of the proposed AMPC based EMS, three different driving cycles which represent different driving situations will be used to evaluate the performance comparing with conventional ECMS method: the New European Driving Cycle (NEDC) which is designed to determined CO2 emissions and fuel economy in passenger cars; a class 2 Worldwide harmonized Light vehicles Test Procedures (WLTC) which is designed to harmonize the worldwide driving behavior from 2015; an urban driving cycle from a Tazzari Zero presented in [11]. The program developed in MATLAB-Simulink^{TM} for the challenge 2017 is used to develop and to test the proposed AMPC which runs on a computer with 2.3GHz working frequency and 8GB RAM.

4.1 Simulation setup

In this paper, some parameters of MPC model are chosen as follows: the length of prediction horizon is 2.5s; the sample time is 0.25s, so p is 10, which can be considered as tuning parameter but not discussed here. The range of SoC_{bat} is from 0.4 to 0.7, the initial value SoC_{bat0} is 0.7, ideal State-of-Charge of battery SoC_r is 0.6 [4]. It has to be reminded that in order to compare different method fairly, the battery will be charged to the initial state at the best efficiency point after driving cycle finished. And some parameters about the fuel cell system can be found in [11]. To adjust the $\omega_{SoC_{bat}}$ with PI controller, the parameters are chosen to be $\omega_0=5$, $K_p=100$, $K_i=1$; based on the experiments of three driving cycles, ω_{ef} and ω_{fc} are chosen as $5\alpha^2, 1$ respectively (α is the EF at the best efficiency point, according to the challenge file, α=259.55).

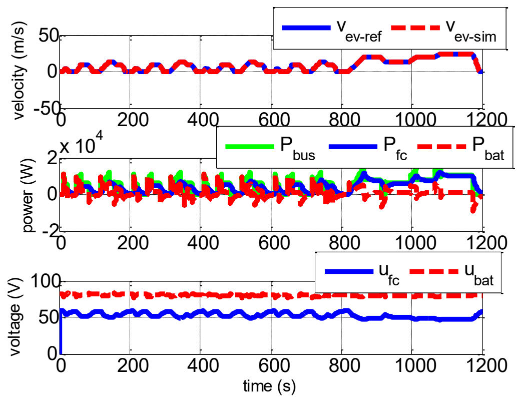

Fig. 4. Vehicle speed, power split, voltage of FC and battery of NEDC.

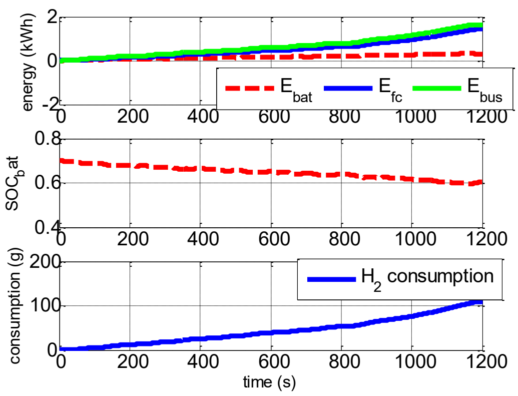

Fig. 5. Energy distribution, the State-of-Charge of battery and the H_2 consumption of NEDC.

4.2 Simulation results

The simulation result over driving cycle NEDC is shown in Figs 4 and 5. Moreover, simulation results of AMPC and ECMS over NEDC, WLTC and Real Urban driving cycle are shown in TABLE II. The power demand (or current demand) is separated according to the proposed AMPC based EMS. The changes of SoC_{bat} is very slow because the penalty weight of battery current is bigger than the FC current, due to reducing the battery degradation which means improve the charge-sustainability. Comparing the performance of ECMS and proposed AMPC presented in TABLE II, the improvement of fuel consumption for three different cycles is 4.86%, 1.80%, 4.71% respectively. The reason for the small improvement of WLTS is possibly inaccuracy of predicted current demand. Considering other performance about charge-sustainability of battery, the battery degradation based on AMPC is decreased by 42.43% averagely comparing with EMS based on ECMS, which means battery degradation is much slower by using ECMS based on AMPC. Meanwhile, the degradation of FC is also reduced by 3.89% averagely, which means that energy sources lifetime (including battery and FC system) is extended. In order to test the adaptivity of proposed method, the scoring driving cycle, which is obtained from a real test drive (2590s) included urban and extra driving, is used in proposed method.

The result shows that the SoC_{bat} fluctuated around the SoC_r and did not passed the limitation. The average computational cost is 0.033s for every optimization cycle.

Table 2. Simulation results of AMPC and ECMS

Driving Cycle	Performance index	ECMS	AMPC
NEDC	SoC_end	0.6033	0.6102
	Battery Degradation	0.7332	0.3434
	FC Degradation	3.0597	2.8976
	Hydrogen cost (g)	139.97	133.17
WLTC	SoC_end	0.6480	0.6050
	Battery Degradation	0.8605	0.4211
	FC Degradation	3.0672	2.9409
	Hydrogen cost (g)	173.36	170.24
Real Urban	SoC_end	0.6215	0.6413
	Battery Degradation	0.5526	0.4253
	FC Degradation	2.6376	2.5779
	Hydrogen cost (g)	54.64	52.07

Note: the value of Battery Degradation and FC Degradation is multiplied by 10^4. The degradation is calculated based on the equations presented in the challenge [11], from 0 (means can not work any more) to 1 (means still new, never be used), no unit.

5. Conclusion

In this paper, a new online energy management strategy for hybrid electric vehicles based on Adaptive Model Predictive Control is proposed to minimize the fuel consumption and increase the energy sources lifetime. This method is a compromise between short-sighted ECMS method and cycle-dependent and computational DP method. During a finite prediction horizon, the proposed method can obtain the optimal control inputs considering the future situation with lower computation intensity. The quadratic cost equation takes fuel economy, battery recharge equivalent cost and charge-sustainability of battery into account. The simulation results of different driving cycles demonstrate that proposed method can minimize the fuel consumption well and extend the lifetime of battery almost 50%. This paper gives a better understanding of MPC and more research will be done about the prediction horizon and adjustment of penalty weights in the future.

6. References

[1] F. Zhang, J. Q. Xi and R. Langari, “An Adaptive Equivalent Consumption Minimization Strategy for Parallel Hybrid Electric Vehicle Based on Fuzzy PI”, IEEE Intelligent Vehicles Symposium (IV), Gothenburg, pp. 460-465, Jun. 2016.

[2] C.C. Chan, A. Bouscayrol and K. Chen, “Electric, Hybrid and Fuel Cell Vehicles: Architectures and Modeling”, IEEE Transactions on Vehicular Technology., vol. 59, no. 2, pp. 589 – 598, Feb. 2010.

[3] D. Chrenko, S. Gan, C. Gutenkunst, R. Kriesten and L. Le Moyne, "Novel Classification of Control Strategies for Hybrid Electric Vehicles," IEEE Vehicle Power and Propulsion Conference (VPPC), Montreal, QC, 2015, pp. 1-6.

[4] H. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, I. V. Kolmanovsky and S. Di Cairano, "MPC-Based Energy Management of a Power-Split Hybrid Electric Vehicle," in IEEE Transactions on Control Systems Technology, vol. 20, no. 3, pp. 593-603, May 2012.

[5] R. M. Patil, Z. Filipi and H. K. Fathy, "Comparison of Supervisory Control Strategies for Series Plug-In Hybrid Electric Vehicle Powertrains Through Dynamic Programming," IEEE Transactions on Control Systems Technology, vol. 22, pp. 502-509, Feb 2014.

[6] X.-C. Zhao, G. Guo,“Survey on Energy Management Strategies for Hybrid Electric Vehicles”, Acta Automatica Sinica, vol.42, no.3, pp. 322-334, Mar 2016.

[7] A. Sciarretta, M. Back and L. Guzzella, "Optimal control of parallel hybrid electric vehicles," in IEEE Transactions on Control Systems Technology, vol. 12, no. 3, pp. 352-363, May 2004.

[8] C. Musardo, G. Rizzoni, Y. Guezennec and B. Staccia, “A-ECMS: an adaptive algorithm for hybrid electric vehicle energy management”, European Journal of Control, Vol. 11, no. 4–5, pp. 509-524, 2005.

[9] H. A. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang and I. V. Kolmanovsky, "Predictive energy management of a power-split hybrid electric vehicle," IEEE American Control Conference, St. Louis, MO, 2009, pp. 3970-3976.

[10] U. Sartori, F. Biral, E. Bertolazzi and S. Onori, "On-Line power management optimization of a hybrid electric vehicle with Non linear MPC and battery re-charge equivalent cost," IEEE IECON, Florence, 2016, pp. 5094-5100.

[11] C. Dépature, S. Jemeï, L. Boulon, A. Bouscayrol, N. Marx, S. Morando, A. Castaings, "IEEE VTS Motor Vehicles Challenge 2017 - Energy Management of a Fuel Cell/Battery Vehicle," IEEE VPPC, Hangzhou, 2016, pp. 1-6.

[12] V. Liso, M. Pagh Nielsen, and S. Knudsen Koer, “Thermal modeling and temperature control of a PEM fuel cell system for forklift application”, Int. Journal of Hydrogen Energy, vol. 39, pp. 8410-8420, Apr. 2014.

[13] M Debert, G. Yhamaillard and G. A Ketfi-herifellicaud, “Predictive energy management for hybrid electric vehicles - prediction horizon and battery capacity sensitivity”, in IFAC Proceedings Volumes, vol. 43, no. 7, pp. 270-275, Jul. 2010.

[14] P. Falcone, F. Borrelli, H. E. Tseng, J. Asgari, and D. Hrovat, “Linear time-varying model predictive control and its application to active steering systems: Stability analysis and experimental validation,” in International journal of robust and nonlinear control, vol. 18, no. 8, pp.862-875, May. 2008.