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ONLINE IDENTIFICATION OF POWER REQUIRED FOR SELF-SUSTAINABILITY OF THE BATTERY IN HYBRID ELECTRIC VEHICLES†

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ABSTRACT

Hybrid electric vehicles have shown great potential for enhancing fuel economy and reducing emissions. Deriving a power management control policy to distribute the power demanded by the driver optimally to the available subsystems (e.g., the internal combustion engine, motor, generator, and battery) has been a challenging control problem. One of the main aspects of the power management control algorithms is concerned with the self-sustainability of the electrical path, which must be guaranteed for the entire driving cycle. This paper considers the problem of identifying online the power required by the battery to maintain the state of charge within a range of the target value. An algorithm is presented that realizes how much power the engine needs to provide to the battery so that self-sustainability of the electrical path is maintained.

1. INTRODUCTION

Hybrid electric vehicles (HEVs) and plug- in HEVs (PHEVs) have attracted considerable attention due to their potential ability to reduce petroleum consumption and greenhouse gas (GHG) emissions. This capability is mainly attributed to: (1) the potential for downsizing the engine; (2) the capability of recovering energy during braking, and thus, recharging the energy storage unit; and (3) the ability to minimize engine operation at speeds and loads where fuel efficiency is low. In addition, hybridization, which typically refers to the power requirements for the electric motor or the degree of electrification, of conventional powertrain systems allows elimination of near idle engine operation, thus enabling direct fuel economy enhancement.

The power management control algorithm in HEVs and PHEVs determines how to split the power demanded by the driver between the thermal and electrical subsystems so that maximum fuel economy and minimum pollutant emissions can be achieved. Developing a power management control algorithm constitutes a challenging control problem and has been the object of intense study for the last 15 years [1]. In the late 1990s, Zoelch and Schroeder [2] presented one of the first methods to optimize the power split and transmission gear ratio in a parallel HEV over a given driving cycle. Since then, significant research efforts have yet focused on optimizing the power management control in HEVs. Baumann *et al*. [3] proposed a method for design and development of HEVs based on a fuzzy- logic controller. Boyali *et al*. [4] presented another heuristic control algorithm for the power split between the IC engine and the motor in a parallel HEV commercial van with front- wheel drive and manual transmission. Sundstrom, Soltic, and Guzzella [5] developed a controller founded on rule- and mode-based optimal control strategies that optimizes the gear shifting in a parallel HEV while maintaining low computational requirements, and achieving low fuel consumption.

A significant amount of work has been proposed on optimizing the power management control in HEVs using the deterministic formulation of dynamic programming (DP). Lin *et al.* [6] used DP to compute the optimal power split between the engine and motor, and the gear shifting in a parallel HEV to minimize fuel consumption and selected emission species over a given driving cycle. The derived control policy was implemented online through rules. Koot *et al.* [7] presented an extensive study on controlling the vehicular electric power system to reduce the fuel use and emissions using DP over a given driving cycle. The control policy was implemented online

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using model predictive control (MPC). Sundstrom, Guzzella, and Soltic [8] used DP in a torque-assist parallel HEV to achieve an optimized hybridization ratio.

The deterministic formulation of DP has been used to benchmark the fuel economy of HEVs by providing the theoretical efficiency that they can achieve over a given vehicle speed profile (driving cycle). DP has been extended to a stochastic formulation to derive an optimal control policy for a family of driving cycles. Lin, Peng, and Grizzle [9] proposed a stochastic DP approach using the discounted cost criterion where the one-stage cost was the weighted sum of fuel consumption, NOx, and particulate matter, with a penalty for state-of-charge (SOC) deviation. The control policy was derived offline by using the policy iteration method. Tate, Grizzle, and Peng [10] used a shortest path stochastic DP formulation to address the minimization of a weighted sum of fuel consumption and tailpipe emissions for an HEV equipped with a dual mode electrically variable transmission, and derived the optimal solution offline by solving a linear program.

Although DP can provide the optimal solution in both the deterministic and stochastic formulation of the power management control problem, the computational burden associated with deriving the optimal control policy prohibits online implementation in vehicles, and it can grow intractable as the size of the problem increases. To address these issues, research efforts have been concentrated on developing online power management algorithms. The main aspects of these algorithms are concerned with the self-sustainability of the electrical path, which must be guaranteed for the entire driving cycle, and the fact that a priori knowledge of the future driving conditions is available. Such algorithms consist of an instantaneous optimization problem that accounts for storage system SOC variation through the equivalent fuel consumption (EFC). The latter is evaluated by considering average energy paths leading from the fuel to the energy storage of the electrical path. Paganelli *et al.* [11] introduced the equivalent consumption minimization strategy (ECMS) that optimizes the power split and gear ratio while assigning a nonlinear penalty function for SOC deviation in a parallel HEV. Sciarretta, Back, and Guzzella [12] proposed an ECMS algorithm in which the EFC is evaluated under the assumption that every variation in the SOC will be compensated in the future by the engine running at the current operating point. Musardo, Rizzoni, and Staccia [13] presented an adaptive ECMS algorithm that periodically computes the equivalence factor and refreshes the control parameters based on the current driving conditions to maximize fuel economy for a parallel HEV. In the aforementioned research efforts and others considered series HEVs (see [14] and the references therein), the SOC of the battery has been used as a component of the HEV state. However, this leads to a significantly large state space with implications for increasing the computational burden associated with solving the power management control problem.

The research objective here is to consider the problem of identifying online the power required by the battery to maintain its SOC within a range of the target value. The SOC is treated as an uncertainty rather than a component of the state and it is correlated to a power demand. An algorithm is presented that realizes how much power the engine needs to provide to the battery so that self-sustainability of the electrical path is maintained.

The remainder of the paper proceeds as follows. Section 2 introduces the proposed method. Section 3 presents the model and the algorithm that can estimate the parameters of the model online. An example of identifying the power in a series HEV is presented in Section 4. Conclusions are drawn in Section 5.

2. PROPOSED METHOD

For our problem formulation, we consider a heavy-duty series HEV (Figure 1) consisting of a diesel engine (373 kW), a generator (220 kW), a motor (200 kW), and a battery (40 Ah capacity). In series mode, the electric motor is the only means of providing the power to the wheels demanded by the driver. The motor draws electric power in combination from the battery and from a generator run by the engine. While the engine in a conventional vehicle may operate inefficiently to satisfy the driver's power demand, e.g., stop- and-go driving, in a series HEV the engine operates only at its most efficient speeds and loads as it is not coupled to the wheels. Thus the engine is no longer subject to the driver's widely varying power demands and can operate at any desired combination of torque and speed. The objective of the power management control problem in a series HEV is to guarantee the self-sustainability of the electrical path. Namely, the control algorithm seeks to maintain the SOC of the battery within its target value while operating the engine efficiently to minimize fuel consumption and emissions. Thus the control policy for the power management controller is the sequence of the amounts of engine power corresponding to the engine's current speed and SOC of the battery.

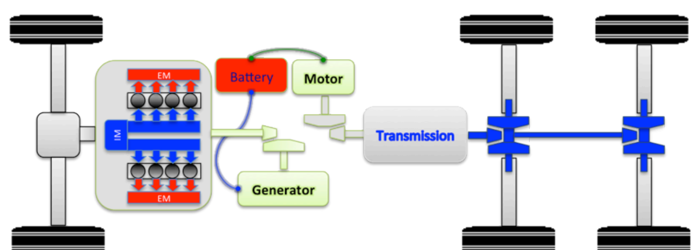

Figure 1. The series hybrid configuration.

In previous research reported in the literature, the SOC of the battery has been used as a component of the HEV state. In our approach, the SOC is treated as an uncertainty (Figure 2), which is correlated to an additional power demand by means of an one-on-one mapping. Depending on the SOC value, there is a corresponding amount of power P_{SOC} that needs to be provided to the battery from the engine to stay at the target SOC. This additional amount is added to the driver's power demand, P_{driver}. To operate the engine under the condition designated by the power management controller, a PID controller regulates the engine torque through the generator. The sequence of the amount of the engine's optimal power, P^*_{engine}, is converted to electrical power through the generator and goes to the battery. The power management controller observes the engine speed and then computes the optimal power that the engine should provide so that to maintain the battery SOC closed to its target value.

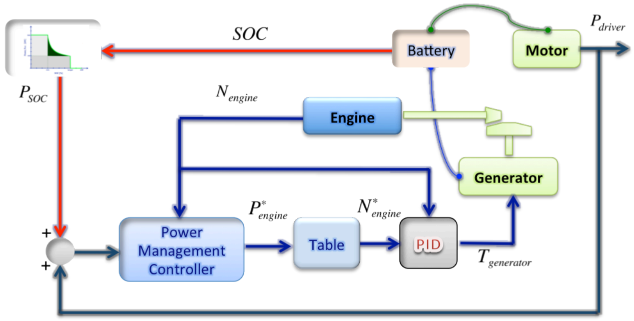

Figure 2. The control scheme for the series hybrid electric vehicle.

We are concerned with identifying online the mapping between the SOC and engine effective power, P_{SOC}, to maintain the SOC of the battery close to its target value. This mapping yields an increasing amount of power, P_{SOC}, as the SOC drops (Figure 3) up to a certain maximum value. This additional amount aims to provide power request from the engine, P_{SOC}, as SOC drops up to a certain minimum SOC designated by battery's specification. If SOC is above the target value, then P_{SOC} is equal to zero as no additional power is required by the battery. In this process, the generator efficiency is not taken into account and the focus is only on operating the engine efficiently.

The range of engine power request, P_{SOC}, between a maximum and a minimum value are designated in conjunction with the optimal brake specific fuel consumption (BSFC) map of the engine. In particular, using the BSFC map, the engine torque corresponding to the minimum BSFC is computed at each different engine speed. Then the optimal engine power with respect to the engine speed can be easily derived, as illustrated in Figure 4. This plot can aim at identifying the appropriate minimum and maximum values of engine power for the mapping between the SOC and P_{SOC}. However, the latter should be different depending on the driver's power demand, P_{driver}. Namely, if the driver's power demand is moderate and doesn't deplete the battery at high rate, then the mapping should be such demanding moderate amount of power for the battery (Figure 3). On the other hand, if the driver's power demand is either high or low, the mapping should indicate higher or lower amount of power respectively intended for the battery, as illustrated in Figure 5 and Figure 6 respectively.

Adjusting online the mapping between the SOC and required amount of battery, P_{SOC}, in conjunction with the driver's power demand can aim at operating the engine efficiently while keeping the SOC of the battery close to its target value. For example, if the driver's power demand is high then SOC drops at high rate, and thus the controller needs to demand high P_{SOC} from the engine to bring it back to the SOC target value (Figure 5). If the driver's power demand is low, then there is no need for the controller to require high amount of power from the engine as the SOC drops at low rate. The mapping between the SOC and P_{SOC} outlined in this section aims to facilitate a mechanism to maintain the self-sustainability of the electrical path in a HEV.

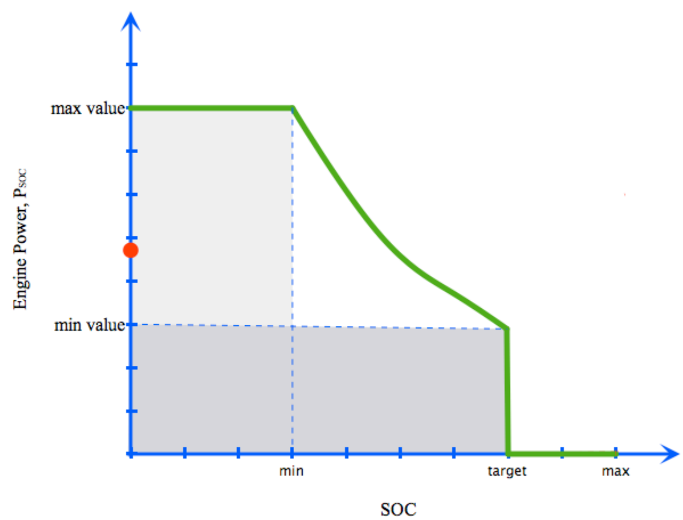

Figure 3. Mapping between the power provided by the engine and the state of charge of the battery when the driver's power demand (red dot) is moderate.

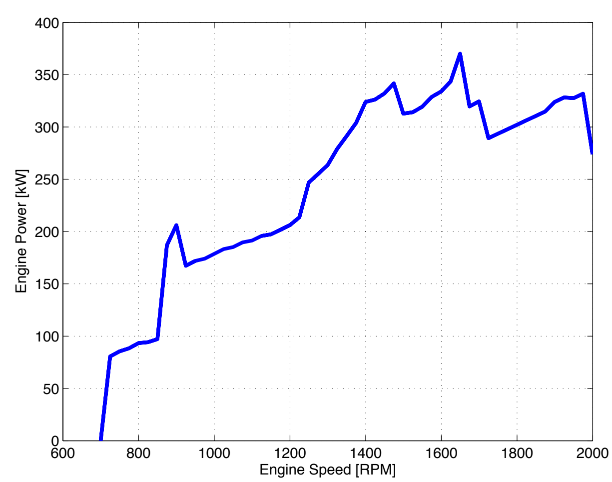

Figure 4. Optimal engine power with respect to the engine speed.

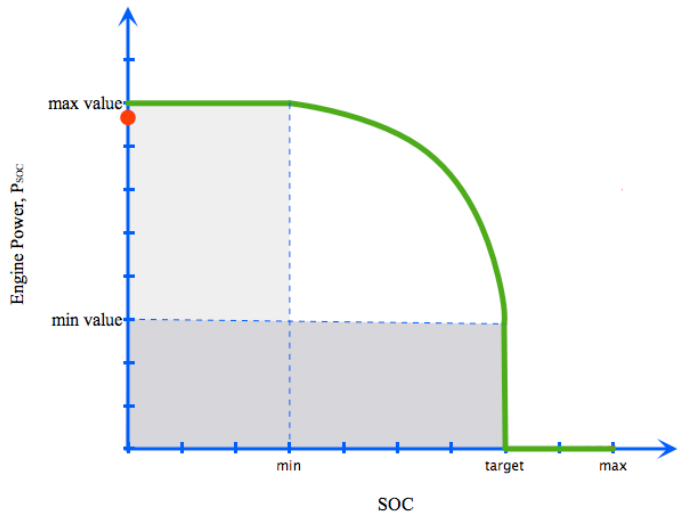

Figure 5. Mapping between the power provided by the engine and the state of charge of the battery when the driver's power demand (red dot) is high.

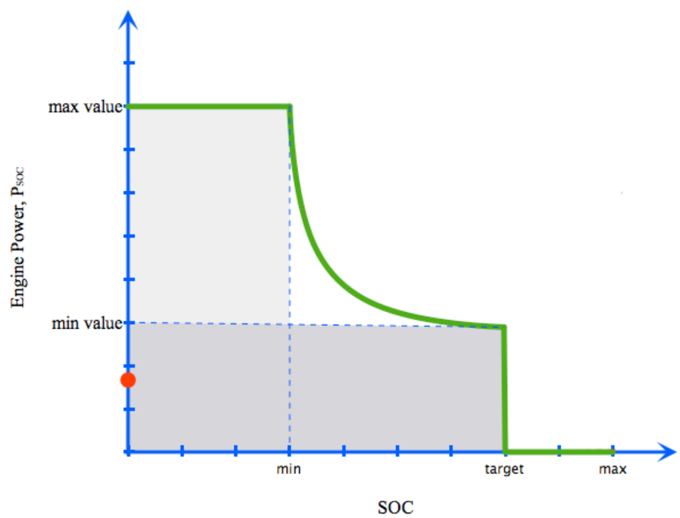

Figure 6. Mapping between the power provided by the engine and the state of charge of the battery when the driver's power demand (red dot) is low.

Thus the objective here is to develop a model that can represent the mapping between the current SOC and P_{SOC}, and an algorithm that will determine the parameters of the model online while the driver drives the vehicle in conjunction with the driver's power demand. For this identification problem we assume that the model is linear in the parameters as described in the next section.

3. IDENTIFICATION MODEL

Modeling of dynamic systems incurring stochastic disturbances for stochastic optimization and control is a ubiquitous task in engineering. A challenging task in this process is to derive mathematical models that can adequately predict the responses of physical systems to all anticipated inputs. Modeling is an essential tool for analyzing sensitivity, assessing uncertainty and for developing algorithms for control and optimization in large complex systems [15]. *Control* involves the modeling, design, and study of a system so that it will accomplish a specified set of objectives or display a certain desired behavior [15]; the latter is known as the *optimization criterion*. A *control policy* is a rule of operation that assigns the controller which actions (decisions) to choose to control a system, and *optimal policy* is one that realizes the goal of the particular optimization criterion of the system.

Exact modeling of dynamic systems, however, may be infeasible or computationally expensive, and thus, deriving an optimal control policy can be impractical [16, 17]. This challenge has increased the need to develop computational models that will allow a system to learn how to improve its performance over time in stochastic environments [18]. Viable approaches have been developed enabling the online implementation of control policies for systems when an accurate model is not available [19, 20]. In this framework, the system interacts with its environment and obtains information enabling it to improve its future performance; namely, optimizing specific performance criteria while satisfying the system's physical constraints. Recently, the theoretical framework and control algorithms were developed to make the engine of a vehicle an autonomous intelligent system capable of learning its optimal calibration in online while the driver is driving the vehicle [21]. Through this new approach, the engine progressively perceives the driver's driving style and eventually learns to operate in a manner that optimizes fuel economy and emissions for that style [22].

For the problem considered here, it seems that the least-squares method is a natural approach for estimating the mapping between the SOC and P_{SOC}. This mapping can be provided through a polynomial model. We assume that the model we want to identify is in the form

$$\hat{y}(i) = \varphi_1(i)\cdot\alpha_1 + \varphi_2(i)\cdot\alpha_2 + \ldots + \varphi_n(i)\cdot\alpha_n\,, \tag{1}$$

where $i = 1,2,\ldots,n, n \in \aleph$, indexes the number of data points, $\hat{y}$ is the output of the model, $\alpha_1,\alpha_2,\ldots,\alpha_n$ are the parameters of the model to be determined, and $\varphi_1,\varphi_2,\ldots,\varphi_n$ are known functions that may depend on other known variables. The model in Eq. (1) can be written in the vector form as follows

$$\hat{y}(i) = \boldsymbol{\varphi}^T(i)\cdot\boldsymbol{\alpha}\,, \tag{2}$$

where $\boldsymbol{\varphi}^T(i) = [\varphi_1(i)\ \ \varphi_2(i)\ \ldots\ \varphi_n(i)]$ and $\boldsymbol{\alpha} = [\alpha_1\ \ \alpha_2\ \ldots\ \alpha_{\boldsymbol{n}}]^T$. This is the *regression model* and the functions $\varphi_i, i = 1,2,\ldots,n$, are called the *regression variables*. The data points correspond to pairs of the measured and regression variables

$\{(y(i),\boldsymbol{\varphi}(i)), i=1,2,...,n, n\in\aleph\}$. The problem is formulated as to minimize the following least squares cost function

$$R(\alpha,n)=\frac{1}{2}\sum_{i=1}^{n}\left[y(i)-\hat{y}(i)\right]^2=\frac{1}{2}\sum_{i=1}^{n}\left[y(i)-\boldsymbol{\varphi}^T(i)\cdot\boldsymbol{\alpha}\right]^2, \quad (3)$$

with respect to the parameters of the model $\alpha_1,\alpha_2,...,\alpha_n$. The measured variable y is linear in parameters α_i and the cost function is quadratic. Consequently, the problem admits an analytical solution. Let $\mathbf{Y}$ and $\hat{\mathbf{Y}}$ be the vector of the measured variables and output of the model respectively

$$\mathbf{Y}=\left[y(1),y(2),...,y(n)\right]^T, \text{ and} \quad (4)$$

$$\hat{\mathbf{Y}}=\left[\hat{y}(1),\hat{y}(2),...,\hat{y}(n)\right]^T, \quad (5)$$

and let $\mathbf{E}$ be the vector of the error $e(i)$ between the measured variable and output of the model

$$\mathbf{E}=\left[e(1),e(2),...,e(n)\right]^T, \quad (6)$$

where $e(i)=y(i)-\hat{y}(i)=y(i)-\boldsymbol{\varphi}^T(i)\cdot\boldsymbol{\alpha}$. Substituting Eq. (6) to Eq. (3) the cost function can be written as

$$R(\alpha,n)=\frac{1}{2}\sum_{i=1}^{n}e(i)^2=\frac{1}{2}\|\mathbf{E}\|^2. \quad (7)$$

Our objective is to derive the vector of the model parameters $\boldsymbol{\alpha}$ that make the error be equal to zero, that is

$$\mathbf{E}=\mathbf{Y}-\hat{\mathbf{Y}}=\mathbf{Y}-\boldsymbol{\Phi}\cdot\boldsymbol{\alpha}=0, \quad (8)$$

where $\boldsymbol{\Phi}(n)=\left[\boldsymbol{\varphi}^T(1)\ \boldsymbol{\varphi}^T(2)\ ...\ \boldsymbol{\varphi}^T(n)\right]^T$. Consequently, the solution of the least squares problem is given by solving Eq. (8), namely

$$\boldsymbol{\alpha}=\left(\boldsymbol{\Phi}^T\cdot\boldsymbol{\Phi}\right)^{-1}\cdot\boldsymbol{\Phi}^T\cdot\mathbf{Y}. \quad (9)$$

If the matrix $\boldsymbol{\Phi}^T\cdot\boldsymbol{\Phi}$ is nonsingular, then the solution of Eq. (9) is a unique minimum for the least squares problem. In our problem, the data points represent the driver's power demand and the functions φ_i represent the SOC.

Let

$$f(n)=\left(\boldsymbol{\Phi}^T\cdot\boldsymbol{\Phi}\right)^{-1}. \quad (10)$$

Then Eq. (9) can be written

$$\alpha(n)=f(n)\cdot\sum_{i=1}^{n}\varphi(i)\cdot y(i). \quad (11)$$

We have

$$f(n)^{-1}=\Phi^T\cdot\Phi=\sum_{i=1}^{n}\varphi(i)\cdot\varphi(i)^T=$$
$$\sum_{i=1}^{n-1}\varphi(i)\cdot\varphi(i)^T+\varphi(n)\cdot\varphi(n)^T=$$
$$f(n-1)^{-1}+\varphi(n)\cdot\varphi(n)^T. \quad (12)$$

From Eqs. (9) and (12) we have

$$\sum_{i=1}^{n-1}\varphi(i)\cdot y(i)=f(n-1)^{-1}\cdot\alpha(n-1)=$$

$$f(n)^{-1}\cdot\alpha(n-1)-\varphi(n)\cdot\varphi(n)^T\cdot\alpha(n-1). \quad (13)$$

Combining Eqs. (11) and (13), the parameters of the model for n data is given by

$$\alpha(n)=\alpha(n-1)-f(n)\cdot\varphi(n)\cdot\varphi(n)^T\cdot\alpha(n-1)+$$
$$f(n)\cdot\varphi(n)\cdot y(n)=$$
$$\alpha(n-1)-f(n)\cdot\varphi(n)\left(y(n)-\varphi(n)^T\cdot\alpha(n-1)\right). \quad (14)$$

Eq. (14) has a strong intuitive appeal as it can update the parameters of the model online and sequentially based on the previous estimate of the parameters without requiring any a priori knowledge of the driver's driving style. The estimate of the model $\alpha(n)$ is obtained by adding a correction to the previous estimate $\alpha(n\text{-}1)$ according to Eq. (14). Thus, starting with a given model (i.e., mapping between the SOC and P_{SOC}) the model is updated online in conjunction with the power demanded by the driver. Namely, depending on the driver's power demand a set of the model's parameters, α, is computed from Eq. (14) resulting in the suitable mapping between the SOC and P_{SOC}. Consequently, the engine can aim to provide the amount of power to the battery through the generator required to maintain the SOC close to the desired target.

4. SIMULATION RESULTS

To validate the effectiveness of the online algorithm, we used Autonomie [23]. Autonomie is a Matlab/Simulink simulation package for powertrain and vehicle model development developed by Argonne National Laboratory. Autonomie provides a variety of existing forward-looking powertrain and vehicle models that can support the evaluation of new control functions in a math-based simulation environment. A vehicle model from Autonomie's database representing a medium duty series HEV configuration, illustrated in Figure 1, was used in this study.

In a series HEV configuration, we can operate the engine at any desired combination of engine torque and speed. The objective of the power management control problem is to operate the engine efficiently to reduce fuel consumption while guaranteeing the self-sustainability of the electrical path, i.e., maintaining the SOC close to its target value, which was 70% in this case. The online identification algorithm that controls the engine is compared to a load following control algorithm, as it has been a popular approach for series HEVs. However, since both controllers yield a suboptimal solution future research should compare the proposed algorithm with other optimal approaches reported in the literature and under different driving cycles.

Both HEVs, the one having the load following controller and the one with the online identification algorithm, were run over the same driving cycle and were able to follow it precisely as shown in Figure 7. The online identification algorithm computed the mapping between the SOC and the power required from the battery P_{SOC}. Depending on the SOC value, the mapping yields the corresponding amount of power P_{SOC} that needs to be provided to the battery from the engine to stay at the target SOC. For the model in Eq. (1) adopted here the vector of functions $\boldsymbol{\varphi}$ was selected to be of a third order as appropriate to capture the one-on-one correlation, namely

$$\varphi^T(i) = \left[x^3(i) \;\; x^2(i) \;\; x(i) \;\; 1\right] \tag{15}$$

where x corresponds to the SOC. The use of a higher order polynomial found to add no additional information for this particular problem. On the other hand, a lower order polynomial found to be not suitable to capture the correlation between the SOC and the power required by the battery to stay close to its target value. The variation of the model along the driving cycle is illustrated in Figure 8.

The selection of the order of the model needs to be defined at the beginning. However, as the SOC varies, and depending on the power required from the driver, the parameters of the model change. To operate the engine under the condition designated by the power management controller, a PID controller regulated the engine torque through the generator as shown in Figure 2. The sequence of the amount of the engine's power, P^*_{engine}, designated by the online identification algorithm was converted to electrical power through the generator and delivered to the battery. The mapping estimated by the proposed algorithm was able to maintain the SOC of the battery close to the target value, as illustrated in Figure 9. With the load following controller, however, the SOC exhibits a significant discrepancy from its target value deemed characteristic of its dependency on the driver's power demand.

The inherent algorithm in Autonomie, called *dichotomy*, was used to compare the simulation results. The algorithm runs the HEV model over the same driving cycle for multiple times and then yields the results corresponding to the same initial and final SOC. Thus the fuel consumption results of the controllers can be comparable. Both HEV models, with the load following controller and the one using the online identification algorithm, run over the same driving cycle multiple times until the initial and final SOC becomes the same.

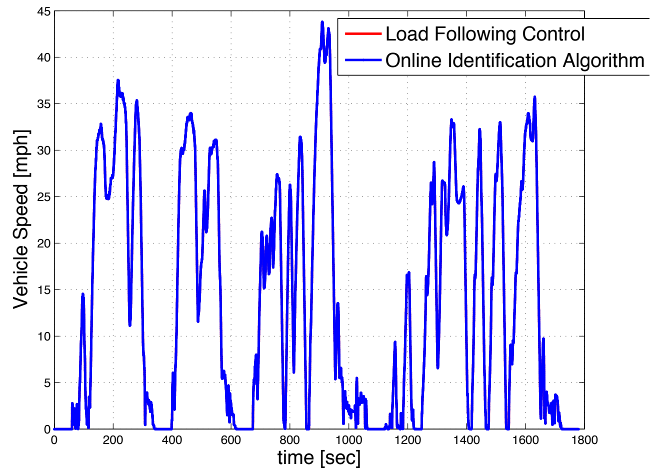

Figure 7. The driving cycle used to simulate the series hybrid electric vehicle model with the two different power management control algorithms.

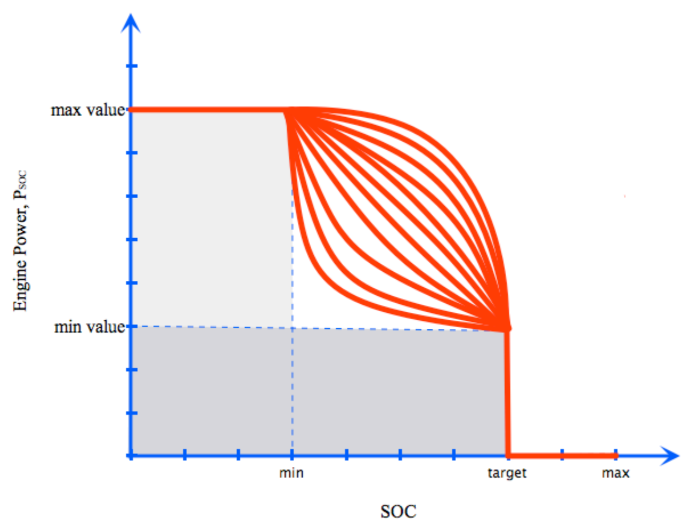

Figure 8. Mapping between the power should be provided by the engine and the state of charge of the battery.

The HEV model with the load following controller ended up with initial and final SOCs of 72.2%, whereas the HEV model using the online identification algorithm ended up with initial and final SOCs of 70.9%. The engine power for both controllers over the driving cycle is illustrated in Figure 10 and Figure 11 (zoom-in). The online identification algorithm is set up to operate the engine up to a certain maximum value based on the optimal engine power with respect to current speed (Figure 4). The maximum value in the mapping was assigned to be 250 kW. As the SOC drops below the target value, the controller increases the engine power as specified by the mapping.

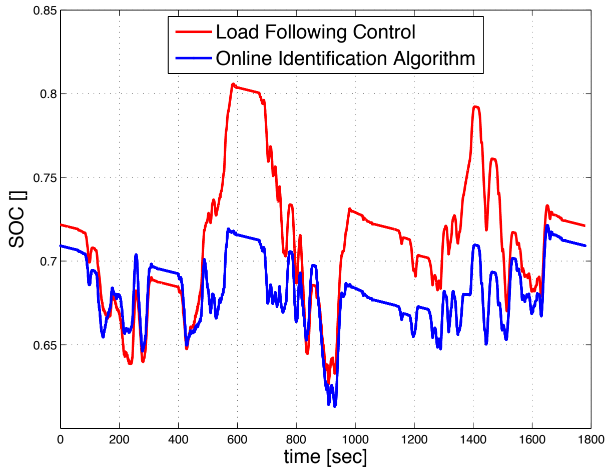

Figure 9. State of charge of the battery variation over the driving cycle with the load following controller and the battery identification algorithm.

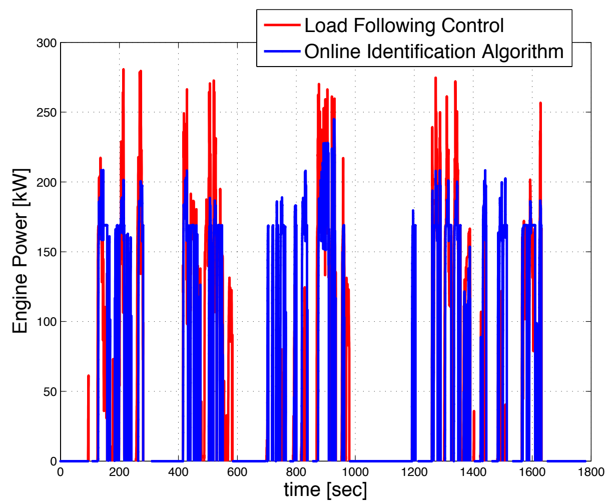

Figure 10. Engine power over the driving cycle with the load following controller and the battery identification algorithm.

With the load following controller, the engine operates at higher power rates directly analogous to the driver's power demand. The online identification algorithm, on the other hand, operates the engine with respect to the current SOC using the mapping between SOC and the optimal engine power with respect to the engine speed (Figure 4). The algorithm can aim at operating the engine efficiently while keeping the SOC of the battery close to its target value. The load following controller, on the other hand, requires an amount of power from the engine corresponding to the power demanded by the driver independently of the current SOC. As a result, it operates the engine under higher power, and thus higher fuel consumption, while SOC exhibits higher deviations from the target value (Figure 9), 70% in this case. As a result, the online identification algorithm operates the engine at lower BSFC values (Figure 12) resulting in a 3.6% cumulative fuel consumption improvement compared to the load following controller, as illustrated in Figure 13. This improvement is attributed due to adjusting online the mapping between the SOC and P_{SOC} in conjunction with the driver's power demand.

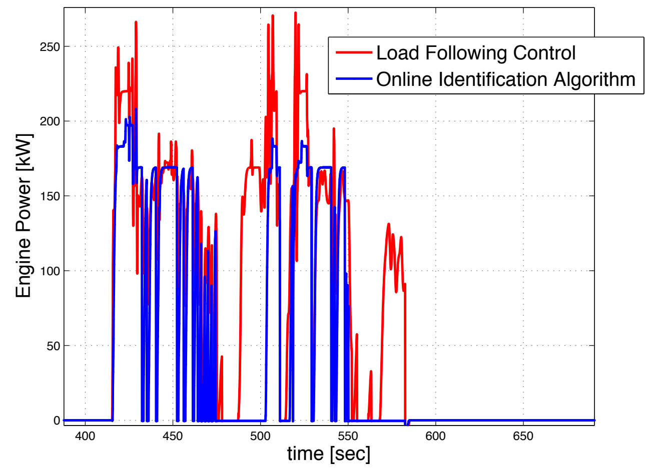

Figure 11. Engine power over the driving cycle with the load following controller and the battery identification algorithm (zoom-in).

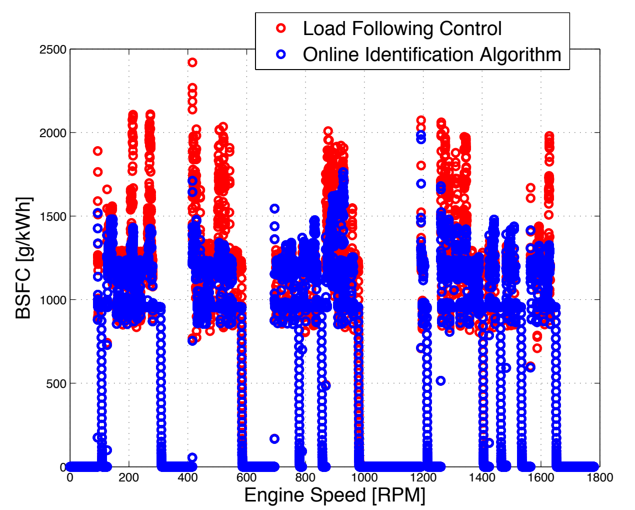

Figure 12. Brake specific fuel consumption (BSFC) values over the driving cycle with the load following controller and the battery identification algorithm.

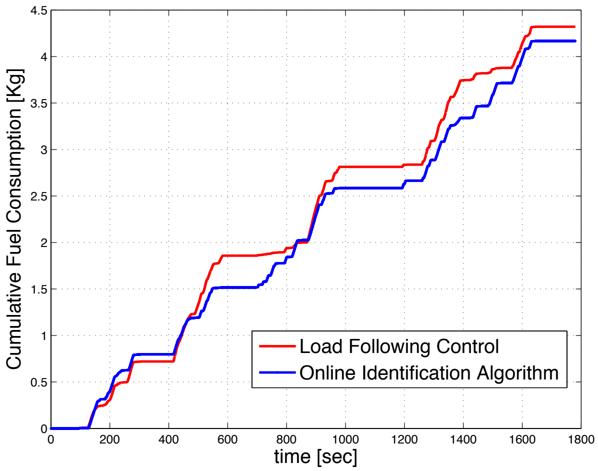

Figure 13. Cumulative fuel consumption over the driving cycle with the load following controller and the battery identification algorithm.

5. CONCLUDING REMARKS

The research reported here aims to facilitate a mechanism to maintain the self-sustainability of the electrical path in a HEV. The paper addressed the problem of identifying online the power required by the battery to maintain the SOC within a range of the target value in a HEV. Although in previous research reported in the literature the SOC has been used as a component of the HEV state, in our approach, it was treated as an uncertainty correlated to an additional power demand by means of one-on-one mapping.

In an example using a series HEV, the algorithm was able to maintain the SOC close to the target value with implications in fuel consumption improvement. The algorithm was compared to the load following control algorithm, as it has been a popular approach for series HEVs. However, since both controllers yield a suboptimal solution future research should compare the proposed algorithm with other optimal approaches reported in the literature and under different driving cycles.

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REFERENCES

[1] A. A. Malikopoulos, "Supervisory Power Managemnet Control Algorithms for Hybrid Electric Vehicles: A Survey," *IEEE Transactions on Intelligent Transportation Systems,* 2014 (in press).

[2] U. Zoelch and D. Schroeder, "Dynamic Optimization Method for Design and Rating of the Components of a Hybrid Vehicle," *International Journal of Vehicle Design,* vol. 19, pp. 1--13, 1998.

[3] B. M. Baumann, G. Washington, B. C. Glenn, and G. Rizzoni, "Mechatronic design and control of hybrid electric vehicles," *IEEE/ASME Transactions on Mechatronics,* vol. 5, pp. 58--72, 2000.

[4] A. Boyali, M. Demirci, T. Acarman, L. Guvenc, O. Tur, H. Ucarol, B. Kiray, and E. Ozatay, "Modeling and control of a four wheel drive parallel hybrid electric vehicle," in *Proceedings of the 2006 IEEE International Conference on Control Applications*, pp. 155--162, 2006.

[5] O. Sundstrom, P. Soltic, and L. Guzzella, "A Transmission-Actuated Energy-Management Strategy," *IEEE Transactions on Vehicular Technology,* vol. 59, pp. 84--92, 2010.

[6] C.-C. Lin, H. Peng, J. W. Grizzle, and J.-m. Kang, "Power Management Strategy for a Parallel Hybrid Electric Truck," *IEEE Transactions on Control Systems Technology,* vol. 11, pp. 839--849, 2003.

[7] M. Koot, J. T. B. A. Kessels, B. de Jager, W. P. M. H. Heemels, P. P. J. van den Bosch, and M. Steinbuch, "Energy management strategies for vehicular electric power systems," *IEEE Transactions on Vehicular Technology,* vol. 54, pp. 771--782, May 2005.

[8] O. Sundstrom, L. Guzzella, and P. Soltic, "Torque-Assist Hybrid Electric Powertrain Sizing: From Optimal Control Towards a Sizing Law," *IEEE Transactions on Control Systems Technology,* vol. 18, pp. 837--849, July 2010.

[9] C.-C. Lin, H. Peng, and J. W. Grizzle, "A stochastic control strategy for hybrid electric vehicles," in *Proceedings of the 2004 American Control Conference*, pp. 4710--4715, 2004.

[10] E. D. Tate, J. W. Grizzle, and H. Peng, "SP-SDP for Fuel Consumption and Tailpipe Emissions Minimization in an EVT Hybrid," *IEEE Transactions on Control Systems Technology,* vol. 18, pp. 1-16, 2010.

[11] G. Paganelli, M. Tateno, A. Brahma, G. Rizzoni, and Y. Guezennec, "Control development for a hybrid-electric sport-utility vehicle: strategy, implementation and field test results," in *Proceedings of the 2001 American Control Conference*, pp. 5064--5069, 2001.

[12] A. Sciarretta, M. Back, and L. Guzzella, "Optimal Control of Parallel Hybrid Electric Vehicles," *IEEE Transactions on Control Systems Technology,* vol. 12, pp. 352--363, 2004.

[13] C. Musardo, S. Benedetto, S. Bittanti, Y. Guezennec, L. Guzzella, and G. Rizzoni, "An Adaptive Algorithm for Hybrid Electric Vehicles Energy Management," in *Proceedings of FISITA World Automotive Conference*, 2004.

[14] A. A. Malikopoulos, "Stochastic Optimal Control for Series Hybrid Electric Vehicles," in *Proceedings of the 2013 American Control Conference*, pp. 1189--1194, 2013.

[15] B. A. Hendrickson and M. H. Wright, "Mathematical Research Challenges in Optimization of Complex Systems," ed: U. S. Department of Energy – Office of Science Workshop Report, 2006.

[16] A. A. Malikopoulos, "Convergence properties of a computational learning model for unknown Markov chains," *J. Dyn. Syst. Meas. Control,* vol. 131, pp. 0410111--7, 2009.

[17] A. A. Malikopoulos, P. Y. Papalambros, and D. N. Assanis, "A Real-Time Computational Learning Model for Sequential Decision-Making Problems Under Uncertainty," *J. Dyn. Syst. Meas. Control,* vol. 131, pp. 0410101--8, 2009.

[18] R. S. Sutton, "Learning to Predict by the Methods of Temporal Difference," *Machine Learning,* vol. 3, pp. 9-44, 1988.

[19] D. P. Bertsekas and J. N. Tsitsiklis, *Neuro-Dynamic Programming (Optimization and Neural Computation Series, 3)*, 1st ed.: Athena Scientific, May 1996.

[20] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction (Adaptive Computation and Machine Learning)*: The MIT Press, March 1998.

[21] A. A. Malikopoulos, P. Y. Papalambros, and D. N. Assanis, "Online identification and stochastic control for autonomous internal combustion engines," *J. Dyn. Sys., Meas., Control,,* vol. 132, pp. 024504--9, 2010.

[22] A. A. Malikopoulos, D. N. Assanis, and P. Y. Papalambros, "Real-time self-learning optimization of diesel engine calibration," *J. Eng. Gas Turbines Power,* vol. 131, pp. 022803--9, 2009.

[23] (Online). *Autonomie*. Available: http://www.autonomie.net/index.html

