ECMS Controller Robustness in Flex-Fuel Hybrid Vehicles

Chris Manzie  
Department of Mechanical Engineering,  
The University of Melbourne,  
Victoria 3010, Australia  
e-mail: manziec@unimelb.edu.au

Olivier Grondin  
Control, Signals, and Systems Department,  
IFP Energies Nouvelles,  
1 et 4, avenue de Bois-Preau,  
Rueil-Malmaison 92500, France  
e-mail: olivier.grondin@ifpen.fr

Antonio Sciarretta  
Control, Signals, and Systems Department,  
IFP Energies Nouvelles,  
1 et 4, avenue de Bois-Preau,  
Rueil-Malmaison 92500, France  
e-mail: antonio.sciarretta@ifpen.fr

Gianluca Zito  
Control, Signals, and Systems Department,  
IFP Energies Nouvelles,  
1 et 4, avenue de Bois-Preau,  
Rueil-Malmaison 92500, France  
e-mail: gianluca.zito@ifpen.fr

Control algorithms for hybrid vehicles have undergone extensive research and development leading to near-optimal techniques being employed and demonstrated in prototype vehicles over the previous decade. The use of different implementations of optimal controllers is inevitably linked through the assumed knowledge of the system being controlled. With the growing interest in alternative fuels, such as ethanol, liquefied petroleum gas (LPG), and compressed natural gas (CNG) due to enhanced emissions and fuel security considerations, a natural extension is to hybridize these engines to improve fuel economy and CO₂ emissions. This step is complicated by the potential variation in fuel composition seen with many gasoline and diesel alternatives, leading to uncertainty in the models used by the hybrid powertrain controller. This work investigates the robustness of one hybrid powertrain optimal control approach, the equivalent consumption minimization strategy (ECMS). Two case studies are performed involving experimentally obtained engine maps from two significantly different prototypes flex-fuel vehicles to quantify the potential impact of map error caused by incorrect fuel assumptions. [DOI: 10.1115/1.4027561]

1 Introduction

Hybridization of vehicle powertrains has been demonstrated to significantly reduce fuel consumption and overall cost of ownership, particularly during urban driving when the opportunity to utilize regenerative braking is highly advantageous relative to conventional powertrains [1]. While tailpipe CO₂ emissions are directly linked to fuel consumption, recent studies, such as Refs. [2] and [3] have also demonstrated that there is also a life-cycle CO₂ benefit to partial powertrain electrification.

The ability of a hybrid vehicle to maximize fuel economy is indelibly linked to the control strategy used to select the utility of the combustion engine and the electric motor. Initial work in this regard utilized rule-based control strategies [4–6], while the integration of optimization [7] and optimal control methodologies [8–12] have led to improvements in fuel economy, particularly in the knowledge of part [13,14] or all [15,16] of the future driving conditions. These optimal control techniques have been readily extended to cope with additional issues facing hybrid electric vehicles, including emissions [17,18], drivability [19], battery charging, and catalyst temperature [20]. Meanwhile a lack of knowledge about the driving cycle has been partially addressed through the incorporation of speed [21] or state-of-charge [22] dependence on the equivalence factor, typically through the integration of a proportional feedback term.

Common to the optimal control approaches is the need to inform the controller certain characteristics about the engine and motor being controlled. The required information is typically quasi-steady, and includes, for example, fuel consumption maps in the case of ECMS [9,23] or efficiency contours under other proposed schemes [13]. Extensions have included consideration of topography [14,24].

Aside from powertrain electrification, there is also significant interest in the use of alternatives to gasoline and diesel to aid in fuel security and improve tailpipe CO₂. Fuels, such as LPG, CNG, and gasoline–ethanol blends, have attracted different levels of regional interest depending on local availability and distribution networks. However, the composition of all these fuels in an engine is subject to high variability. For instance, LPG can vary from almost pure propane to equal proportions of propane and butane; while ethanol engines may encounter blends ranging from E0 to E85.

On a vehicle with only an alternative-fuel internal combustion engine, this compositional variation leads to a detuning of the engine calibration to ensure sufficient robustness for all the possible fuels that may be encountered. One experimental study on an ethanol engine by Ref. [25] found up to a 3% efficiency gain could be obtained by using optimized spark advance for E85 over the gasoline (E0) setpoints. Similarly, a 2–3.6% loss in efficiency using LPG of varying compositions was attributed to the fuel timing in a diesel engine in Ref. [26].

If the alternative-fuelled engine is integrated into a hybrid vehicle, there is another level of consideration as the aforementioned model-based controllers all rely on quasi-steady maps that are potentially incorrect. Given the possible CO₂ advantages afforded by combining hybrid powertrains with an alternative fuel, the robustness of the existing algorithms, and indeed their ability to deliver close to optimal performance in the presence of map uncertainty, is an open question.

This paper sets out to analyze the general problem of using uncertain fuel models in an ECMS controller. The degradation in performance is then quantified for two very different prototype flex-fuel hybrid vehicles developed to run on ethanol blends ranging from E5 to E85. The primary outcome of this work is to assess the need for updated hybrid control strategies that cope with varying fuel composition and to quantify the level of performance degradation that may be encountered. A tangential outcome is the identification of the CO₂ potential of hybrid and dedicated ethanol-blended powertrains, which may be utilized in other lifecycle studies to help ascertain the long-term benefits of the technology.

2 Local Robustness Analysis of ECMS

Quasi-steady models for instantaneous fuel and battery charge consumption, $f(t, u)$ and $q(t, u)$, respectively, are typically used in a general Hamiltonian-based controller design [8–11,22,23,27,28] for a hybrid powertrain with control inputs $u$ at time $t$. The
cumulative consumption of fuel, $m_t$, and charge, $q$ after $T$ seconds of driving is then

$$m_t = \int_0^T f(t, u)dt$$  \hspace{1em} (1)

$$q = \int_0^T g(t, u)dt$$  \hspace{1em} (2)

In a typical parallel hybrid implementation, the input $u$ may represent the engine torque, while for generator and some series-hybrid implementations, the decoupling of the engine from the wheels means both engine torque and speed may be selected. Considering only equivalent fuel consumption, the resulting Hamiltonian and optimal control chosen from permissible inputs in the (potentially time varying) set $U_i$ are

$$H(f, g, u, t) = f(t, u) + s(t)g(t, u)$$  \hspace{1em} (3)

$$u^*(t) = \arg \min_{u \in U_i} H(f, g, u, t)$$  \hspace{1em} (4)

As noted in Ref. [27], Eq. (3) is effectively an equivalent charge optimization metric with the Lagrange multiplier $s(t)$ representing the fuel-electricity equivalence, leading to it being denoted the equivalence factor.

**Assumption 1.** The values of $u^*(t)$ form dense subsets of the allowable input range, $u^* \in U^*_i \subset U_i$ containing the point of maximum engine efficiency, $s^\text{peak}$, and zero engine torque. Furthermore, the average engine efficiency within the subset containing $s^\text{peak}$ is given by $\eta_\text{av} = (1 - \gamma)\eta^\text{peak}$, where $\gamma \in [0, 1]$.

**Remark 1.** Ideally, the optimal inputs will be clustered around regions of high engine efficiency whenever the engine is on. The density of the inputs in the efficiency space will be influenced by the vehicles torque demand arising from the driving cycle as well as the presence and severity of any operational constraints placed on the controller. The value of $\gamma$ will be affected both by the density of the inputs and the gradients in both the fuel and electrical usage maps used by the controller, $f(t, u)$ and $g(t, u)$.

Now consider that the quasi-steady fuel consumption map used in the controller is perturbed by a static map, $\Delta f(t, u)$, i.e., the map used by the controller is $f(t, u) := f(t, u) + \Delta f(t, u)$. Uncertainties in the electrical path and driveline of hybrid vehicles are much less common, and so perturbations to $g(t, u)$ are not considered here.

The resulting control, $\bar{u}$, obtained using the ECMS strategy on the perturbed map is described by

$$\bar{H}(\bar{f}, g, u, t) = \bar{f}(t, u) + \bar{s}(t)g(t, u)$$  \hspace{1em} (5)

$$\bar{u}^*(t) = \arg \min_{u \in U_i} \bar{H}(\bar{f}, g, u, t)$$  \hspace{1em} (6)

The following assumption is now introduced for all three maps relevant to the performance of the ECMS controller.

**Assumption 2.** The quasi-steady maps are sufficiently well approximated at each engine speed, $N_e$, by the following equations:

$$f(u, t) = \frac{1}{2}a_0(N_e(t))u^2 + b_0(N_e(t))u + c_0(N_e(t))$$  \hspace{1em} (7)

$$g(u, t) = \frac{1}{2}a_1(N_e(t))u^2 + b_1(N_e(t))u + c_1(N_e(t))$$  \hspace{1em} (8)

$$\Delta f(u, t) = \frac{1}{2}a_2(N_e(t))u^2 + b_2(N_e(t))u + c_2(N_e(t))$$  \hspace{1em} (9)

For ease of notation, the speed-dependence of the coefficients in Eqs. (7)–(9) is omitted in the following discussion. The following additional assumptions are now placed on the perturbation map and driving cycle.

**Assumption 3.** The parameters of the perturbation map $a_2, b_2$, and $c_2$ are small.

**Remark 2.** The assumption of quadratic maps with only small perturbations in practice limits discussion to a local analysis as a quadratic fit across the entire operating range of the engine is unlikely, albeit in conjunction with Assumption 1 this will be about the point of maximum engine efficiency.

**Assumption 4.** The driving cycle is of length $T$ and completely known a priori. Furthermore, it does not invoke battery state-of-charge constraints.

**Remark 3.** Assumption 4 implies the equivalence factors, $s^*$ and $\bar{s}^*$, are constants that can be numerically determined offline through a dichotomous search for the value that maintains battery state of charge at the end of the cycle [8].

**Theorem 1.** Under Assumptions 1–4, using an ECMS strategy with an incorrect fuel map parameterized by $a_2$, $b_2$, and $c_2$, there exists $\beta \in R$ such that the fuel consumption penalty is bounded by

$$\Delta m(a_2, b_2, c_2) \leq (1 - \gamma)\int_0^T \beta(s_1^2 + s_2^2 + s_3^2)dt$$  \hspace{1em} (10)

Sketch of proof: The fuel penalty for using incorrect map, $\Delta m_i$, is

$$\Delta m_i = \int_0^T f(\bar{u}^*(t)) - f(u^*(t))dt$$  \hspace{1em} (11)

The Hamiltonians and resulting minimizing controls, $u^*$ and $\bar{u}^*$ for the true and perturbed systems may be calculated utilizing Assumption 2, which results in the term within the integrand being expressed in terms of $a_0, b_0, a_2, b_2, s^*$, and $\bar{s}^*$. These latter terms are constant by Assumption 4, but implicitly depend on $c_0$ and $c_2$.

To remove the implicit dependence, Assumption 1 is used to find $u^*$ in terms of the input for peak efficiency. With Assumption 2 and recognizing peak efficiency occurs when $(du/ds)_f = 0$, a solution for $s$ and $\bar{s}^*$ in terms of known parameters can be ascertained and Eq. (11) is expressed in terms of known parameters.

Finally, applying a Taylor series expansion of the term in the integrand, utilizing the triangle inequality and from Assumption 3, there exists a constant $\beta$ such that the higher order terms in the expansion are upper bounded by the linear expressions, and the result of the theorem follows directly.

**Remark 4.** In the event that the driving cycle is unknown and the equivalence factor is estimated online, the dependence on the perturbation parameters may change as there are additional feedback dynamics involved. The actual performance degradation will be additionally influenced by both the structure of the $s^*$-estimator algorithm and the gains used within it.

**Remark 5.** The same steps may be followed to establish the relative fuel economy penalty, i.e., $\Delta m_i/m_i$ in which case the relative sizes of the parameter perturbations ($a_2/a_0, b_2/b_0$, and $c_2/c_0$) replace the absolute values in Eq. (10).

3 Overview of Engine and Simulator

Theorem 1 states small perturbations in the fuel maps lead to small fuel consumption penalties. To test the veracity of the assumptions and the result, two vehicles developed within IFP Energies Nouvelles are used as real world case studies. The first vehicle (vehicle A) is a parallel hybrid demonstrator for flex-fuel Energies Nouvelles are used as real world case studies. The first vehicle (vehicle A) is a parallel hybrid demonstrator for flex-fuel

064504-2 / Vol. 136, November 2014 Transactions of the ASME

---

Downloaded From: http://dynamicsystems.asmedigitalcollection.asme.org/ on 12/18/2014 Terms of Use: http://asme.org/terms
four-cylinder, 1.346 l spark ignition engine with a five speed automated transmission.

The second vehicle (vehicle B) has a more conventional electrical configuration for parallel hybrid operation, with a similar size motor but much smaller Li-ion battery pack (42 kW and 1.5 kWh, respectively). It has a turbocharged, four-cylinder 2.0 l spark ignition engine with slightly lower compression ratio, and also a five speed automated transmission. The key parameters of each vehicle are summarized in Table 1.

Static calibrations to tune the engine control variables were performed on a dynamometer for ethanol blends E5 and E85, and the consumption maps concurrently determined. The difference in fuel flow rate maps for the two compositions, $\Delta \nu$, is shown in Fig. 1 for different engine speeds. From these maps, it appears that limiting the approximation of $\Delta \nu$ to a quadratic in torque for fixed engine speed appears reasonable except in the (rarely used) high torque regions on the F4R engine.

The size of the parameters in the polynomial approximations of $\Delta \nu$ varies with operating point and fuel map, with the average values across all engine speed expressed in both absolute and relative to the original mappings in Table 2. It is apparent that for the ET3 engine used in vehicle A, the perturbation parameters $a_2$ to $c_2$ are significantly smaller relative to the $a_0$ to $c_0$ than for the other engine. The implication of this in terms of the validity of Assumption 3 and consequently Theorem 1 will be investigated.

For further insight, the efficiency contour maps are shown in Figs. 2 and 3. From these, it is clear that despite the relatively linear characteristic observed for the $\Delta \nu$ contours, the maximal efficiency for each composition is obtained under quite different operating points in each engine. For example, the ET3 engine operating on E5 has a degradation in efficiency past a torque of around 85 Nm across all speed ranges, while under E85, the peak efficiency is obtained at the highest torques. Similarly, the efficiency peak for the F4R engine is at a medium torque and high speed running on E5, but this shifts to a medium speed and high torque when E85 fuel is used. This unexpected result was attributed to the effects of turbocharging and the additional engine controllers required. The implications of utilizing an engine not specifically designed for hybrid applications and its associated controllers’ warrants further exploration but are beyond the scope of this investigation.

The simulator used in this work is a version of the Hy-HIL environment developed within IFP Energies Nouvelles and used extensively in the development and testing of hybrid powertrain controllers [28–30]. It includes detailed electrical and mechanical modeling capability, with efficiencies of both paths realistically prescribed from experimental testing. The driving cycles used during testing included two standard regulatory cycles, the New European Drive Cycle (NEDC) and the Federal Test Procedure (FTP) cycles, and one more representative of real world driving, the world harmonized light duty test procedure (WLTP) [31].

Preliminary simulations over these driving cycles involved the vehicles solely powered by the internal combustion engines. The vehicles are able to match all three cycles on engine power alone, and thus any future restriction of the parallel hybrid’s use of the engine is due to driveability considerations. The fuel consumption and CO2 released for the different compositions over the cycles are provided in Table 3, with the latter estimated using standard fuel properties and linearly interpolating between 0 and 100% ethanol.

The increase in fuel consumption with the increased ethanol content reflects the decrease in lower heating value of the fuel, however although there is a significantly larger proportion of fuel used for E85 relative to E5, the CO2 benefits of high ethanol fuel are clear.

4 ECMS Robustness Case Studies

4.1 Generator Case. Initially, both the engine torque and speed are considered free variables, representing either a generator operating at fixed speed and load in a distributed electricity network or in some series-hybrid implementations. While constant operation at a fixed point does not strictly require the use of an online ECMS algorithm, it does provide an interesting benchmark for the influence of map uncertainty on fuel economy as it quantifies the term in the integrand of Eq. (10) as the parameter describing the spread of operating points, $\gamma$, is equal to zero.

The efficiency maps in Figs. 2 and 3 may be denoted as $\eta_\theta (u, N_e)$ for a fuel with ethanol fraction $\theta$. It follows that the optimal operating point is $(u_{\theta, \text{opt}}, N_{e, \text{opt}}) := \arg_{u, N_e} \max \eta_\theta (u, N_e)$.
and so the fuel penalty from incorrect composition information may be expressed as a percentage according to

\[ D_m(\%) = \frac{\eta_{\text{peak}}(\phi^*, N^*_{\text{e,\phi}})}{\eta_{\text{peak}}(\phi^*, N^*_{\text{e,\phi}})} \times 100\% \]  

(12)

For the ethanol blends E5 and E85 used on the ET3 engine, the percentage of fuel loss is shown in Table 4, and it indicates that a 4–5% loss is incurred for constant operation using the incorrect map. Note that these figures do not consider the additional losses of up to 3% incurred by running the engine at suboptimal engine setpoints (e.g., non-MBT spark timing), and thus the penalty for not considering fuel composition in the different control strategies may be as high as 8%.

On the other hand, the results are significantly different for the F4R engine. While the peak efficiency is almost identical on both fuel blends, using the incorrect setpoint can lead to a fuel consumption penalty of over 30% when the E85-optimal setpoint is used with E5 fuel. However, the shape of the efficiency maps for the two fuel blends (Fig. 3) leads to a much lower 3.6% degradation if the E5-optimal setpoint is used with E85 fuel.

4.2 Parallel Hybrid Cases With Known Driving Cycles. Theorem 1 predicts small errors in the fuel maps should lead to proportional degradation in the fuel economy, with the spread of operating points represented by \( \gamma \) also playing a role. With the fuel map errors introduced by incorrect assumptions of the ethanol–gasoline blend, simulations are now conducted for both parallel hybrids. As only vehicle A appears to satisfy Assumption 3, the validity of the theorem for vehicle B is questionable.

Controller constraints are included explicitly during the simulations, and play a role in determining the validity of Assumption 1. The imposed constraints are typical of those in real world implementation, and include limiting gear selection, consideration of alternator limitations, and state-of-charge usage to ensure drivability and battery management requirements are maintained. However, these are limited to constraints at the ECMS-controller level; due to the quasi-steady nature of the simulation environment, it is not possible to consider the impact of engine-level control constraints (e.g., knock limits) and so these are assumed to be already captured by the quasi-steady maps.

Assumption 4 enables the ECMS controller to calculate and use the optimal fuel-electricity equivalence factor, which is obtained offline through an iterative numerical search. An initial guess for
a constant $s^*$ on a given cycle was used in conjunction with the engine maps to solve Eqs. (3) and (4) at each point in the cycle. The state-of-charge deviation at the end of the cycle was then used to update the guess for $s^*$ and the process repeated until the state-of-charge deviation was within nominal tolerance bounds. The state-of-charge constraints were not encountered for either vehicle over any of the tested cycles. The fuel maps and equivalence factor were synchronized, so that use of the incorrect fuel information involves both the matched (but incorrect) map and equivalence factor.

The results of the simulations over three cycles are given in columns 3 and 4 of Table 5 for both vehicles. An initial comparison with Table 3 reveals that the potential fuel economy gain through hybridization in the range of 15–25%. Furthermore, although not shown directly in this table, the CO2 levels are below 120 g/km from all drive cycles for both vehicles in all but one case, and with the E85 fuel blend, the CO2 production is below 65 g/km.

For vehicle A, it is clear that the fuel penalty incurred is not significant with no combination of cycle and incorrect information yielding greater than 1.5% degradation in economy, thereby validating the result of Theorem 1, albeit with only Assumptions 2–4 verified at this stage.

To investigate the validity of Assumption 1, the engine operating points for the simulations when the engine is running on E5 fuel and the ECMS controller has both the correct and incorrect fuel information on the WLTP cycle are plotted in Fig. 4. The average engine efficiency when the correct fuel information is available is 35.4%, which represents a 8% penalty relative to the peak of 38.2% from Table 4. Thus, although, there appears a wide distribution of points in the figure, in an efficiency context, the distribution is actually quite dense. This is also true when the incorrect fuel information is used as average operating efficiency for the points in the right-hand side of Fig. 4 degrades to only 35.1%. Consequently, Assumption 1 is valid for vehicle A.

It is already known that vehicle B does not satisfy Assumption 1 and consequently small fuel degradation cannot be expected with incorrect fuel information. As might be reasonably expected, the observed fuel economy degradation is significant in two of the drive cycles when E5 fuel is used but the controller assumes E85 fuel is present, with 8% and 12% fuel economy degradation observed. The low degradation in the case of the NEDC cycle is attributable to the comparatively low number of operating points in the cycle not allowing a comprehensive exploitation of the degrees of freedom available to the controller.

This leads to the interesting anecdotal observation that assuming the fuel is E5 irrespective of its actual composition would appear to be a safe choice for both vehicles. A second anecdotal observation arises if Tables 4 and 5 are compared, and does suggest that a reasonable approximation of the fuel economy penalty incurred through incorrect fuel maps in the ECMS controller of a parallel hybrid may be obtained from the generator percentage losses scaled by approximately 75%. A more accurate assessment of the validity of this estimate would require more vehicles and drive cycles to be considered.

### Table 3: Simulated fuel consumption using ICE-only propulsion

<table>
<thead>
<tr>
<th>Driving cycle</th>
<th>Fuel blend</th>
<th>Fuel consumption (l/100 km)</th>
<th>CO2 (g/km)</th>
<th>Fuel consumption (l/100 km)</th>
<th>CO2 (g/km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEDC</td>
<td>E5</td>
<td>5.60</td>
<td>12.44</td>
<td>8.82</td>
<td>196.7</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>8.37</td>
<td>72.5</td>
<td>12.59</td>
<td>109.0</td>
</tr>
<tr>
<td>FTP</td>
<td>E5</td>
<td>5.72</td>
<td>127.6</td>
<td>9.66</td>
<td>215.4</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>7.99</td>
<td>69.2</td>
<td>13.82</td>
<td>119.7</td>
</tr>
<tr>
<td>WLTP</td>
<td>E5</td>
<td>6.14</td>
<td>136.9</td>
<td>8.14</td>
<td>181.6</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>8.57</td>
<td>74.2</td>
<td>11.61</td>
<td>100.5</td>
</tr>
</tbody>
</table>

### Table 4: Percentage of fuel loss from incorrect map use for generator case

<table>
<thead>
<tr>
<th>Case 1: ET3</th>
<th>Case 2: F4R</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Efficiency</strong></td>
</tr>
<tr>
<td><strong>ET3 engine</strong></td>
<td></td>
</tr>
<tr>
<td>$\eta_{e5}^{\text{peak}}(\delta_{E5},\delta_{N_E5})$</td>
<td>38.2</td>
</tr>
<tr>
<td>$\eta_{E5}(\delta_{E5},\delta_{N_E5})$</td>
<td>36.1</td>
</tr>
<tr>
<td>$\eta_{e5}^{\text{peak}}(\delta_{E5},\delta_{N_E5})$</td>
<td>40.9</td>
</tr>
<tr>
<td>$\eta_{E5}(\delta_{E5},\delta_{N_E5})$</td>
<td>39.2</td>
</tr>
</tbody>
</table>

### Table 5: Simulated fuel consumption and fuel losses attributed to incorrect assumption on fuel maps and equivalence ratio used by ECMS controllers

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Actual</th>
<th>Assumed</th>
<th>Fuel consumption (l/100 km)</th>
<th>$\Delta \eta_t$</th>
<th>Fuel consumption (l/100 km)</th>
<th>$\Delta \eta_t$</th>
<th>Fuel consumption (l/100 km)</th>
<th>$\Delta \eta_t$</th>
<th>Fuel consumption (l/100 km)</th>
<th>$\Delta \eta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEDC</td>
<td>E5</td>
<td>E5</td>
<td>4.61</td>
<td>—</td>
<td>4.61</td>
<td>—</td>
<td>4.62</td>
<td>—</td>
<td>4.62</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E5</td>
<td>E85</td>
<td>4.66</td>
<td>1.1%</td>
<td>4.67</td>
<td>1.2%</td>
<td>4.69</td>
<td>1.5%</td>
<td>4.68</td>
<td>1.4%</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E5</td>
<td>6.46</td>
<td>—</td>
<td>6.47</td>
<td>—</td>
<td>6.48</td>
<td>—</td>
<td>6.51</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E85</td>
<td>6.51</td>
<td>0.6%</td>
<td>6.61</td>
<td>2.2%</td>
<td>6.55</td>
<td>1.1%</td>
<td>6.62</td>
<td>1.7%</td>
</tr>
<tr>
<td>FTP</td>
<td>E5</td>
<td>E5</td>
<td>4.26</td>
<td>—</td>
<td>4.11</td>
<td>—</td>
<td>4.27</td>
<td>—</td>
<td>4.18</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E5</td>
<td>E85</td>
<td>4.32</td>
<td>1.5%</td>
<td>4.43</td>
<td>7.9%</td>
<td>4.33</td>
<td>1.4%</td>
<td>4.47</td>
<td>7.0%</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E5</td>
<td>5.97</td>
<td>—</td>
<td>5.69</td>
<td>—</td>
<td>5.94</td>
<td>—</td>
<td>5.83</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E85</td>
<td>6.00</td>
<td>0.5%</td>
<td>5.76</td>
<td>1.2%</td>
<td>5.99</td>
<td>0.8%</td>
<td>5.89</td>
<td>1.0%</td>
</tr>
<tr>
<td>WLTP</td>
<td>E5</td>
<td>E5</td>
<td>5.21</td>
<td>—</td>
<td>5.13</td>
<td>—</td>
<td>5.23</td>
<td>—</td>
<td>5.15</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E5</td>
<td>E85</td>
<td>5.27</td>
<td>1.2%</td>
<td>5.73</td>
<td>11.8%</td>
<td>5.29</td>
<td>1.1%</td>
<td>5.77</td>
<td>12.0%</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E5</td>
<td>7.31</td>
<td>—</td>
<td>7.12</td>
<td>—</td>
<td>7.32</td>
<td>—</td>
<td>7.13</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>E85</td>
<td>E85</td>
<td>7.40</td>
<td>0.7%</td>
<td>7.21</td>
<td>1.2%</td>
<td>7.37</td>
<td>0.7%</td>
<td>7.21</td>
<td>1.0%</td>
</tr>
</tbody>
</table>
As a final case study, removal of the drive cycle information from the ECMS algorithm was investigated, i.e., Assumption 4 was relaxed. This is again more representative of a real world deployment where the drive cycle is not available to the controller. The influence of drive cycle information on the fuel economy was expected if the maps used in the ECMS algorithm do not reflect the actual driving conditions. The robustness of the ECMS algorithm was investigated theoretically under quite restrictive assumptions, and it was found that the adaptive estimation of equivalence factor does not result in any significant change to the observed fuel economy when the drive cycles are known. The first vehicle satisfied all assumptions and demonstrated good robustness of the hybrid controller with observed fuel penalties less than 1.5% for use of incorrect maps over a number of considered driving cycles. The second vehicle did not satisfy the required assumptions of the theoretical problem, and exhibited large increase in fuel consumption up to 12% on different driving cycles. Using adaptive ECMS strategies with prior driving cycle information had negligible impact on these results.

5 Conclusion

The robustness of the ECMS algorithm was investigated theoretically under quite restrictive assumptions, and it was found that for vehicles satisfying the assumptions only a small impact on the fuel economy was expected if the maps used in the ECMS algorithm were incorrect. Two case studies were conducted on vehicles with flex-fuel hybrid powertrains, with both vehicles emitting under 120 gCO₂/km and 65 gCO₂/km across all considered driving cycles on E5 and E85 fuel, respectively.

The first vehicle satisfied all assumptions and demonstrated good robustness of the hybrid controller with observed fuel penalties less than 1.5% for use of incorrect maps over a number of considered driving cycles. The second vehicle did not satisfy the required assumptions of the theoretical problem, and exhibited large increase in fuel consumption up to 12% on different driving cycles. Using adaptive ECMS strategies with prior driving cycle information had negligible impact on these results.

### References


