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Fuel economy improvements for urban driving: Hybrid vs. intelligent vehicles

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Abstract

The quest for more fuel-efficient vehicles is being driven by the increasing price of oil. Hybrid electric powertrains have established a presence in the marketplace primarily based on the promise of fuel savings through the use of an electric motor in place of the internal combustion engine during different stages of driving. However, these fuel savings associated with hybrid vehicle operation come at the tradeoff of a significantly increased initial vehicle cost due to the increased complexity of the powertrain. On the other hand, telematics-enabled vehicles may use a relatively cheap sensor network to develop information about the traffic environment in which they are operating, and subsequently adjust their drive cycle to improve fuel economy based on this information – thereby representing 'intelligent' use of existing powertrain technology to reduce fuel consumption. In this paper, hybrid and intelligent technologies using different amounts of traffic flow information are compared in terms of fuel economy over common urban drive cycles. In order to develop a fair comparison between the technologies, an optimal (for urban driving) hybrid vehicle that matches the performance characteristics of the baseline intelligent vehicle is used. The fuel economy of the optimal hybrid is found to have an average of 20% improvement relative to the baseline vehicle across three different urban drive cycles. Feedforward information about traffic flow supplied by telematics capability is then used to develop alternative driving cycles firstly under the assumption there are no constraints on the intelligent vehicle's path, and then taking into account in the presence of 'un-intelligent' vehicles on the road. It is observed that with telematic capability, the fuel economy improvements equal that achievable with a hybrid configuration with as little as 7 s traffic look-ahead capability, and can be as great as 33% improvement relative to the un-intelligent baseline drivetrain. As a final investigation, the two technologies are combined and the potential for using feedforward information from a sensor network with a hybrid drivetrain is discussed.

Keywords: Hybrid vehicles; Intelligent vehicles; Automated driving; Road infrastructure; Telematics

1. Introduction

There are many developments in the automobile industry that will act to improve safety, manufacturability and economy of future production vehicles by a quantum step relative to currently available vehicles. Over the

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majority of the past century, the automobile drivetrain has been principally based around an internal combustion engine, and the engine development over this period ensures that the technology is very mature-meaning significant gains in areas such as fuel economy are no longer readily achievable through further refinement. While fuel cells may 1 day replace the internal combustion engine, the current durability, in-service efficiencies and, most significantly, the cost of fuel cells (an 80 kW fuel cell contains more than $US50,000 of platinum) mean that the market is unlikely to see production fuel cell vehicles for decades. However, the advent of hybrid electric drivetrains offers the capacity to improve fuel economy by using an electric motor to reduce the fluctuating energy requirements of the internal combustion engine without unduly sacrificing vehicle performance. All the major automotive OEMs have developed or are developing hybrid vehicles to add to their fleet, with the earliest models centred around smaller cars including the Toyota Prius and Honda Insight and Civic, while larger passenger cars such as a hybrid Ford Escape and various Lexus models have been released. Despite the benefits in fuel economy offered by hybrid vehicles, the primary disadvantage of the technology from the consumer's perspective is the initial cost can be as much as 70% more than an equivalently powered internal combustion engine-only vehicle.

As well as the technology changes internal to the vehicle, the telematics revolution of the past decade has generated the possibility for a vehicle to communicate with the road infrastructure and other vehicles to obtain greater information about the traffic environment in which it is operating. Systems such as the PATH program (see e.g. Tomizuka, 1994; Rajamani et al., 2000) have demonstrated that platooning of vehicles in an Automated Highway System can lead to increased driver safety, decreased road congestion (increased throughput) and improved fuel economy (not only through improved traffic flow but also through reduced wind resistance through traveling in a platoon (Barth, 2000)). In these types of systems, the demonstrated performance has relied primarily on inter-vehicle communication and passive lane position information through the use of magnetic sensors and consequently vehicle mounted magnetometer arrays.

With fuel consumption in urban environments up to 50% higher than during highway driving, there are even greater possibilities in addressing this area of operation. While integrating platoons of fully automated vehicles in a highway environment relies primarily on the logistics of vehicle interaction, it is a more difficult problem to automate driving in an urban environment given the greater potential system uncertainties such as pedestrians and potential road obstacles. As a result, a first-generation 'intelligent' vehicle operating in an urban environment could be envisaged as providing a driver aid through look-up displays of recommended speeds or routes, rather than a complete driver replacement system, a principle that is similar to the concept of adaptive cruise control systems acting as a precursor to automated platooning scenarios. In either driver aid or replacement scenarios, there is a requirement that the intelligent vehicle must obtain information about some degree of traffic flow from the environment.

If only local traffic information is relevant, this may be provided completely on-board the vehicle itself through the use of radar and laser technologies. Such devices are already used in adaptive cruise control systems, but do not guarantee the string stability necessary for safe platooning of vehicles (Swaroop and Hedrick, 1996). Incorporation of telematics providing the information between vehicles over a dedicated radio bandwidth would not only address this issue in the long term, but also provide information to the vehicle about traffic flow over a larger distance than if each vehicle were operating completely autonomously.

To obtain even greater information to the vehicle over a longer look ahead distance it is most likely that some form of communication between the infrastructure and the vehicle is required. Presently, systems such as Signal Coordination in Regional Areas of Melbourne (SCRAM) in Australia obtain information about traffic flows in urban environments automatically for use in scheduling traffic signals, so it is conceivable that this information could be made available to a suitably equipped vehicle. The information transfer from the network to the vehicle will also have clear advantages in route selection, as discussed in Levinson (2003). The information regarding traffic flow is assumed available in this study, however the algorithms required to fuse data from the different sources are readily discussed in the literature, e.g. (Durrant-Whyte et al., 1990).

Although the reduction of vehicle emissions in urban areas represents a similarly worthwhile goal, the focus of this study is on the relative fuel economy benefits possible using hybrid and communication technologies. The comparison can be used to trade-off the difference between adopting the expense of new technology within the vehicle hardware (i.e. a hybrid powertrain) and within the vehicles environment (i.e. an intelligent infrastructure). The ADVISOR software package (Wipke et al., 1999) provides a deterministic simulation environment in which detailed information over specified drive cycles can be obtained, and is used in this paper to calculate the fuel economy for the different vehicle types.

This paper is organized as follows: in Section 2, the drive cycles and baseline test vehicle are introduced and then used in the development of an optimal hybrid vehicle that maintains all the capabilities of the conventional drivetrain. In Section 3, the future traffic flow the vehicle will encounter is used to adjust the velocity profile of the vehicle itself. A vehicle position algorithm is developed and the resulting fuel economy compared to that achievable over three standard drive cycles. In Section 4, the intelligent vehicle's position is constrained relative to the vehicle in front in order to simulate the effect of having conventional vehicles on the road at the same time as intelligent vehicles. As a final point of interest, in Section 5 the potential for incorporating intelligence into a hybrid vehicle is investigated and discussed with a view to shaping future research directions.

2. Drive cycles and vehicle models

2.1. Drive cycles

Three different urban drive cycles, the US FTP drive cycle without the repeated hot start phase (Samuel et al., 2002), the Economic Commission of Europe cycle with Extra Urban Drive Cycle (ECE-EUDC) (Samuel et al., 2002) and the Australian Urban, or Melbourne Peak cycle (Watson et al., 1982) are used in this work, and are illustrated in Fig. 1. Although the European Drive Cycle is commonly used for regulatory work, it is worth noting that cyclical driving patterns are not considered representative of real world driving scenarios (Samuel et al., 2002; Watson and Milkins, 1986). In contrast, the other two cycles are based on real world driving behaviour, and subsequently more weight is placed on the results obtained using these cycles during this study.

2.2. Modelling the conventional vehicle

The baseline vehicle chosen for this study was a 4-l production family sedan, a decision made since approximately 30% of the vehicle sales in Australia each year are of a similar size and power to the model used here. The block diagram of the conventional drivetrain vehicle model used in ADVISOR is shown in Fig. 2.

It is important to note that the simulation essentially works in a reverse direction to what happens in the real world – that is, the drive cycle is the input to the vehicle model, and the required changes to the vehicle speed are calculated based on the drive cycle. This change in vehicle speed is then converted to engine speed and torque requirements by taking into account the current gear ratio (a shifting map is supplied to the model) and the efficiencies of the transmission. The fuel use is then calculated from a look-up table of fuel rate against engine operating point (defined by engine speed and torque). The key specifications used in the vehicle model are listed in Table 1, while the fuel use map as a function of operating point was adapted from steady state maps provided in Liu (1992) and is illustrated in Fig. 3.

2.3. Modelling the hybrid vehicle

A parallel hybrid configuration was assumed for modelling the hybrid electric vehicle in this study. This configuration consists of an electric motor (EM) and internal combustion engine that can simultaneously or individually drive the transmission (and subsequently propel the vehicle). The split is determined by the vehicle's hybrid control strategy, and in this case a simple default strategy was used which (subject to constraints on the battery state of charge) uses the EM for slow city driving condition and assists the engine for peak acceleration, hill climbing, and extremely fast highway driving conditions. Furthermore, the EM can act in reverse mode to become a generator during regenerative braking and consequently used to recharge the batteries. The structure of the hybrid simulation model is shown in Fig. 4.

In order to accurately compare fuel economy with the conventional powertrain vehicle presented in the previous section, the hybrid vehicle dimensions and properties should be maintained, with the obvious exception of the internal combustion engine being downsized and replaced by a hybrid drivetrain. The necessary sizing of the hybrid vehicle's internal combustion engine is directly coupled to the size of the electric motor used, and

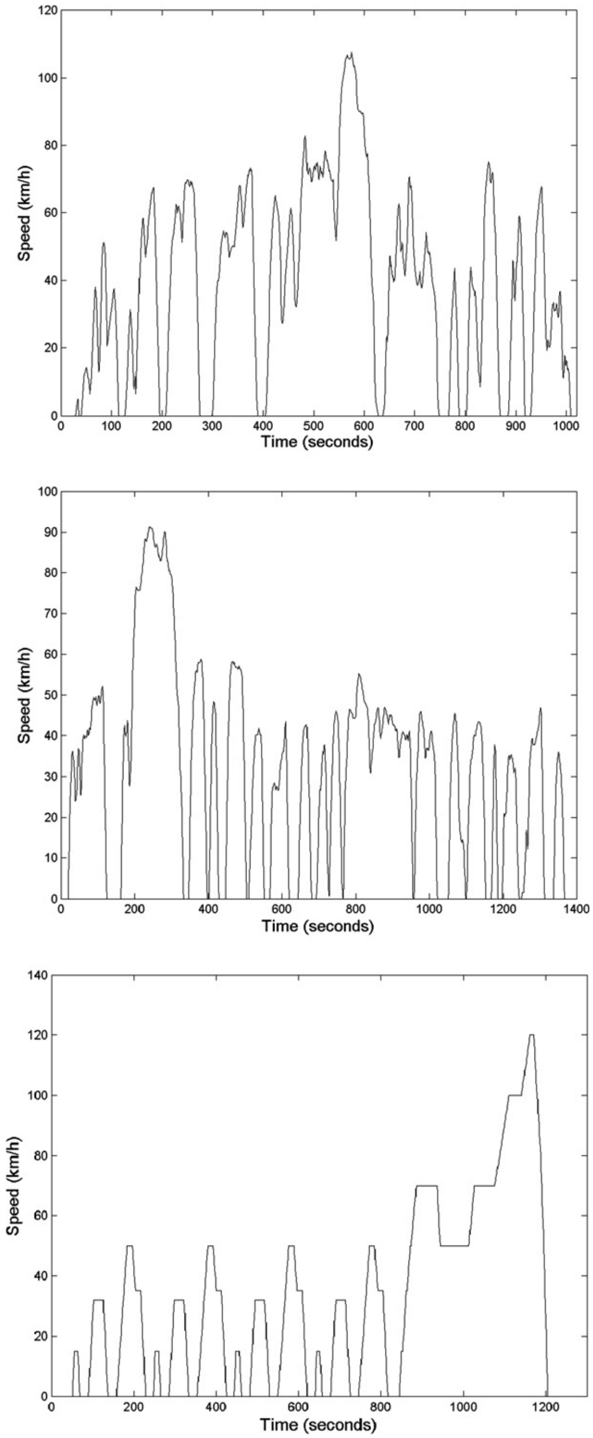

Fig. 1. Australian urban (top) US FTP (middle) and ECE-EUDC (bottom) drive cycles.

hence an optimization process is required to ensure that the configuration is capable of meeting the performance requirements of the vehicle but in doing so uses the minimum amount of fuel. The performance requirements of the conventional drivetrain were set as constraints on the optimization process and are listed in Table 2. Another constraint during the optimization process is the change in state of battery charge at the beginning

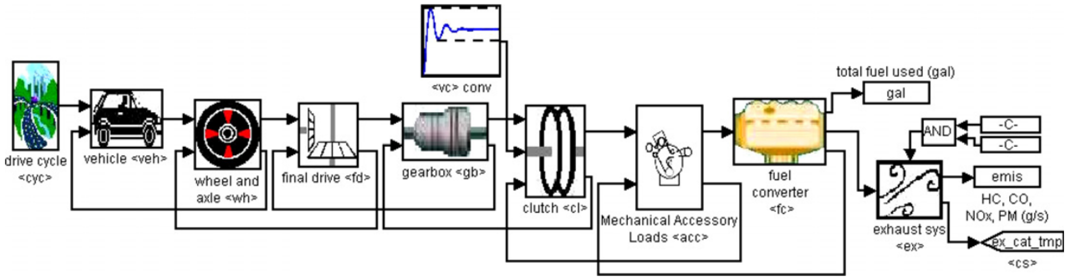

Fig. 2. Block diagram of conventional drivetrain.

Table 1
Conventional vehicle model specifications

Total weight	1642 kg
Chassis weight	1000 kg
Frontal area	2.45 m^2
Coefficient of Drag	0.366
Vehicle weight distribution	Front 55%, rear 45%
Centre of mass height	0.5 m
Vehicle length	5.00 m
Transmission	Manual, 5 speed
Transmission efficiency	95% (constant through all gears)
Gear ratios	3.5:2.14:1.39:1:0.78
Final drive ratio	2.92
Gear changes	$1 \rightarrow 2$ and $2 \rightarrow 1$ @ 24 km/h
	$2 \rightarrow 3$ and $3 \rightarrow 2$ @ 40 km/h
	$3 \rightarrow 4$ and $4 \rightarrow 3$ @ 64 km/h
	$4 \rightarrow 5$ and $5 \rightarrow 4$ @ 75 km/h
Tyre rolling radius	0.314 m
Tyre inertia	8.923 kg.m^2
Tyre pressure, T_p	240 kPa

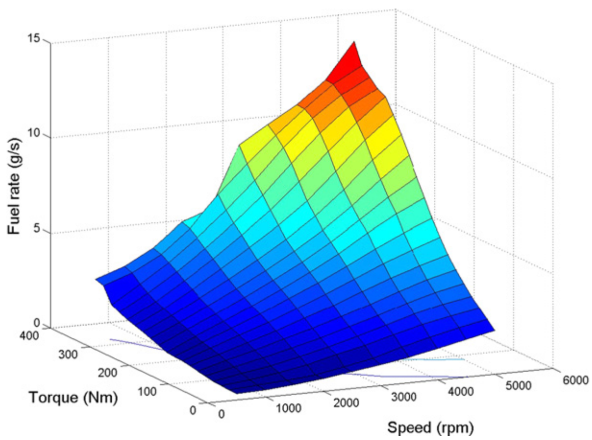

Fig. 3. Fuel consumption map of the test vehicle as a function of operating point.

and end of the cycle to prevent misleading fuel economy results arising from excessive use of the electric motor (which would then require battery replenishment and subsequently increased fuel use the next time the vehicle is run).

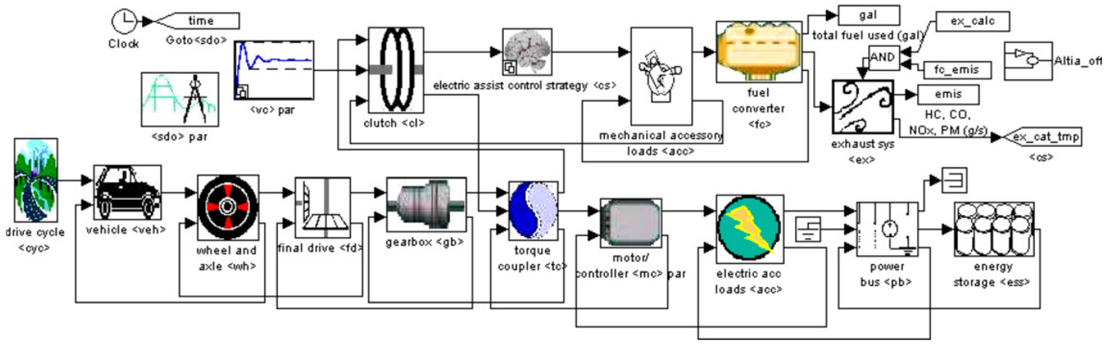

Fig. 4. Block diagram of parallel hybrid configuration.

Table 2
Performance constraints imposed upon hybrid vehicle

	Description	Performance
Acceleration	0–100 km/h	⩽8.5 s
	64.4–100 km/h	⩽3.5 s
	0–137 km/h	⩽16 s
	Maximum acceleration	⩾3.8 m/s^2
	Maximum speed	⩾210 km/h
Gradeability	Sustain 88.5 km/h for 82 s towing 1000 kg load	⩾15.5%
State of charge	Difference between initial and final battery state of charge	⩽ 0.5%

Having identified the constraints to be placed on the hybrid vehicle, the next point to consider is the type of electric motor and internal combustion engine to use as base models for scaling. After consideration of an earlier study (Rosenkranz et al., 1986) it was decided that a 1.3 l, 71 kW turbocharged GM Opel engine would be a suitable starting point for the hybrid's ICE. This choice was motivated by the result that after turbocharging a small engine, the output power is increased by 30–40% relative to the non-turbocharged engine of the same size. This subsequently allows a smaller engine and hence lower frictional losses in comparison to a larger engine supplying the same amount of power as the turbocharged one. Furthermore, by using a smaller capacity engine, the weight can be reduced. A 49 kW Honda permanent magnet brushless DC motor was chosen as the base motor to be scaled and the electric power was provided through NiMH battery modules.

As a result there are three factors that can influence the total performance of the baseline hybrid vehicle – the scaling of the ICE, the scaling of the motor and the number of battery modules used. Naturally increasing the power output of the powertrain components and the number of batteries also increases their weight, and hence will impact on fuel economy. In order to get the best performance of the hybrid vehicle, the engine configuration was optimized over a given drive cycle in order to find the best motor size, number of battery modules and engine size.

The optimization process now represents a constrained multidimensional problem that is not easily solved. In Lim (2004), a particle swarm approach was used to optimize the configuration for fuel economy over different driving cycles, and the result validated against other evolutionary computation algorithms. It was found that with more urban driving conducted in the drive cycle then a larger electric motor could provide more assistance in reducing fuel consumption. As the focus of this paper is on urban driving cycles, the optimum configuration for the urban drive cycles is used subject to meeting the constraints of expressed in Table 2. The optimized vehicle configuration is listed in Table 3, and a fuel use map of the scaled engine is shown in Fig. 5. It is worth noting that the optimized configuration corresponds to an almost equal split in power between the electric motor and the internal combustion engine, which agrees with the 'conventional wisdom' for hybrid configurations used in urban cycles. However, it is recognized that a production vehicle would probably have a larger internal combustion engine to electric motor ratio in order to achieve a balance

Table 3
Results of optimization for hybrid vehicle configuration

Internal combustion engine power (scaled from turbocharged 1.3 l, 71 kW engine)	66 kW
Electric motor power (scaled from 49 kW Honda Permanent Magnet Brushless Motor)	68 kW
Number battery modules (*D* size 1.2 V NiMH 6 cells per module)	194

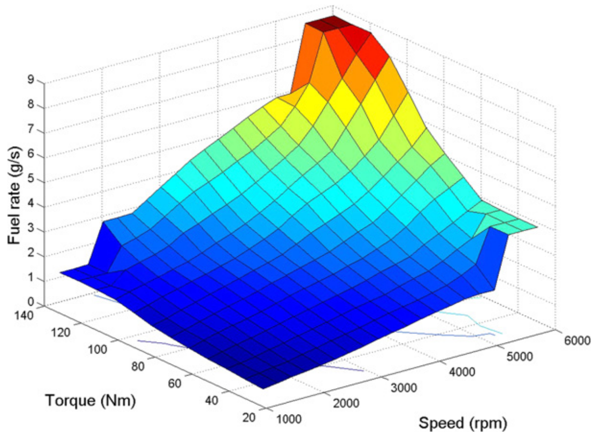

Fig. 5. Fuel consumption map of the turbocharged engine used in hybrid powertrain.

Table 4
Fuel economies for conventional and optimized hybrid vehicles

Drive cycle	Fuel economy (L/100 km)		Improvement with hybrid (%)
	Conventional drivetrain	Hybrid drivetrain[a]	
Australian urban	11.9	10.1	15.3
US FTP	10.8	8.2	24.7
ECE-EUDC	10.6	8.5	19.8

[a] Change in battery state of charge constrained to <0.5%.

between urban and highway cycles. As a consequence, the real-world hybrid fuel economies would be lower than observed in this study.

Having obtained an optimized hybrid configuration, this vehicle was then simulated through all the urban drive cycles with the restriction that the state of charge of the battery at the end of the drive cycle must be within 0.5% of the state of charge at the beginning. The results are provided in Table 4, and demonstrate an average 20% fuel economy improvement across the drive cycles achieved through hybridization. However, these numbers must be qualified to some degree. Firstly, it is recalled that (in the interests of a fair comparison with a conventional drivetrain) the performance of the hybrid must satisfy the constraints given in Table 2. A relaxation of part or all of these constraints will result in further improvements in the fuel economy of the hybrid vehicle, as would improvements in the vehicle's coefficient of drag (both key parts of Toyota's fuel economy strategy for the Prius). Conversely, the concentration on urban drive cycles in the optimization procedure results in an almost equal ratio between the electric motor and internal combustion engine power, which is unlikely to occur in production for a family sedan of this size. Despite these limitations, Table 4 does allow a benchmark to be set against which the fuel economy of the intelligent vehicle can be measured.

3. The intelligent vehicle: a conventional drivetrain with telematics

One of the most significant contributors to fuel use in an urban environment is the stop start behaviour of traffic flow. Through the use of telematics, a given vehicle can be made aware of the traffic and infrastructure in which it is operating and adjust the driving condition en route. Communication between a fleet of vehicles has been utilized in Automated Highway Systems previously (e.g. PATH) in order to improve the overall behaviour of a platoon of vehicles in response to changing traffic conditions. Thus it is assumed for the intelligent vehicle in this paper that there exists a sensor network potentially incorporating inter-vehicle communication, radar and laser technologies that can be used to convey information about the surrounding traffic. This traffic preview information can then be used to adjust the vehicle's instantaneous velocity, whilst arriving at the destination at he same time as an un-equipped vehicle.

It is assumed that the output of the sensor network is assumed to be previewed traffic velocity information, $v_p(t)$, which is available up to T_p seconds ahead of the current time. This allows the position of a vehicle subjected to this traffic flow to be predicted based on its current position, $x(t)$. The following algorithm outlines how the intelligent vehicle may utilize the feedforward traffic information to adjust its own speed to minimize vehicle accelerations.

Intelligent Vehicle Velocity Modification (IVVM) Algorithm (unconstrained case)

Estimate vehicle position at time T_p in the future according to:

$$\hat{x}(t+T_p) = x(t) + \alpha \sum_{i=1}^{T_p/\Delta} v_p(t+i\Delta)\Delta \tag{1}$$

where Δ is the sampling period (considered uniform) and α is a conversion constant. In order to reach this predicted position with minimum stop–start behaviour the intelligent vehicle should attempt to use a constant speed, $v_{int}(t)$, calculated as follows:

$$v_{int}(t) = \frac{\hat{x}(t+T_p) - x(t)}{\alpha T_p} \tag{2}$$

This process, using Eqs. (1) and (2), is repeated every time new information becomes available. In the drive cycles used in this study, this period corresponds to once per second.

It is important to note that a critical assumption in this algorithm is that fuel use is linearly proportional to engine speed for a given torque requirement. Examination of the fuel use maps (shown in Figs. 3 and 5) indicates this is a reasonable assumption for relatively small changes in engine speed providing the current gear is maintained. In the event that there was a highly non-linear relationship between fuel use and engine speed, it may be necessary to consider engine-dependent strategies.

As an example of the alternative drive cycle, Fig. 6 demonstrates the difference if the unconstrained IVVM algorithm is applied to the drive cycles with preview information about traffic flow from the next 50 s. This corresponds to an average 450 metre distance over the US drive cycle, and could conceivably be achieved through on-board sensing and inter-vehicle communication only. While fuel economy minimization is the main outcome, there are further potential advantages to offset the cost of incorporating this technology into a vehicle such as enhanced safety features including crash avoidance or protection, and improved safety at blind crossings (Tsugawa, 2002).

The amount of traffic preview information was varied from 0 to 180 s and the modified driving behaviour using the vehicle velocity modification algorithm was then calculated for each of the US, Australian and ECE-EUDC cycles. While the traffic flow up to the preview time is simply assumed known in this study, it is highly likely that a preview of three minutes would require information transfer between the infrastructure and the vehicle, and consequently greater telematic capability on-board the vehicle (and therefore higher overall vehicle cost). The fuel economy was then measured following simulation over the modified drive cycles and the results are plotted as a function of preview time in Fig. 7. For comparison the fuel economy over the drive cycle if a hybrid vehicle without telematics capability also appears in the figure.

In all three cycles, quite significant improvements in fuel economy can be seen even for relatively short traffic previews. Interestingly, it shows that the improvement in fuel economy is much more marked for the two drive cycles believed to better represent real world driving scenarios. Furthermore, there appears to be a 'knee-point' at approximately 50 s traffic preview beyond which the rate of improvement in fuel economy for extra

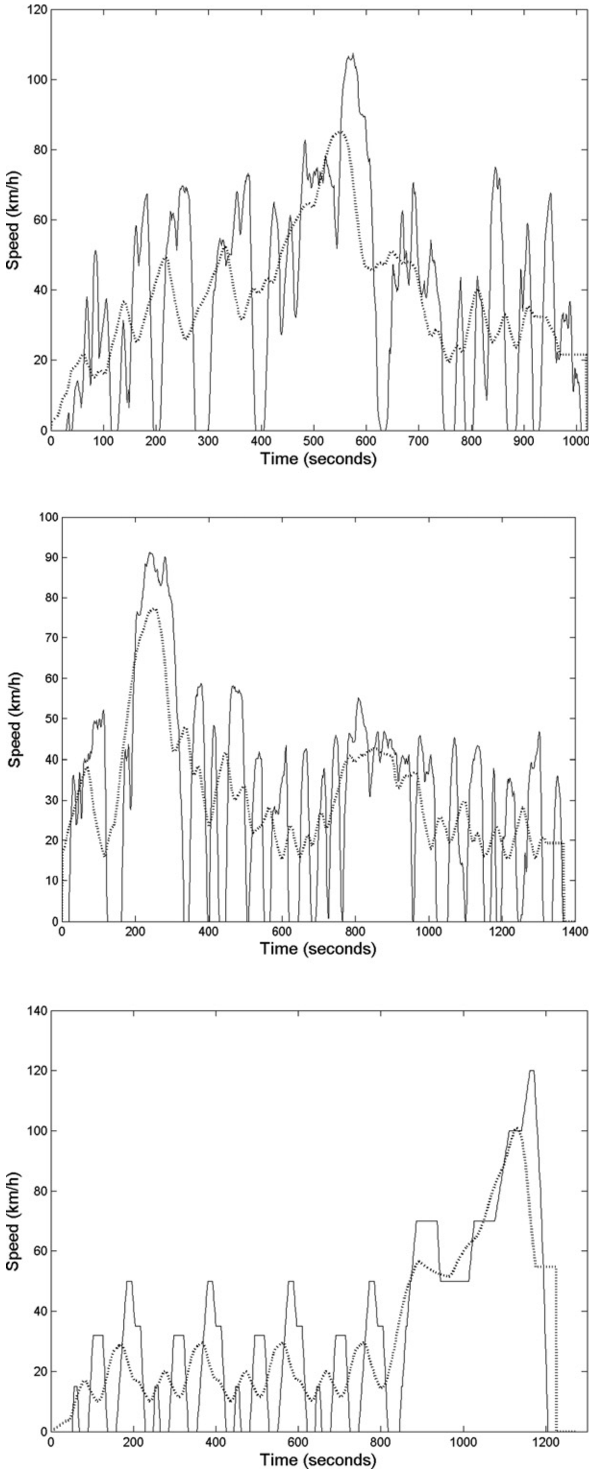

Fig. 6. Urban drive cycles (solid) and after use of 50 s traffic preview information (dotted).

preview information decreases. A quantitative comparison of several key statistics of these plots is presented in Table 5. This data appears to reinforce that telematics realistically represents a more cost effective and

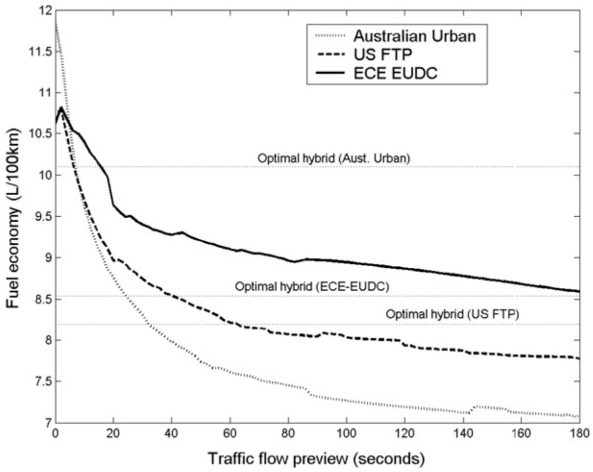

Fig. 7. Fuel economy as a function of preview information over different urban drive cycles. The fuel economies for the optimal hybrid over the same drive cycles are also shown for comparison.

Table 5
Quantitative comparison of fuel economy for varying degrees of feedforward traffic information

Drive cycle	Fuel economy (L/100 km)					Traffic preview for hybrid-equivalent fuel economy
	$T_p = 0$	$T_p = 50$	% change[a]	$T_p = 180$	% change[a]	
Australian Urban	11.8	7.7	35	7.1	40	7
US-FTP	10.8	8.4	22	7.8	28	60
ECE-EUDC	10.6	9.2	13	8.6	19	182

[a] Change is calculated relative to no traffic preview ($T_p = 0$).

significant way of delivering improved fuel efficiencies in passenger vehicles. This notion is further strengthened when it is recalled that the hybrid vehicle model used in this study is optimized for urban driving with a near equal split in the power capability of the internal combustion engine and the electric motor. A further fuel economy benefit of incorporating telematics not accounted for here may be achievable through closer inter-vehicle spacing made possible by automated highway systems resulting in a reduced coefficient of drag for each vehicle (other than the lead vehicle in the platoon). In Barth (2000), the improvements in fuel economy solely through reduced drag coefficients inherent in a platooning situation were estimated to be in the range 5–15% over highway cycles.

However, there are some limitations of this study so far in assessing the performance of the intelligent vehicles. Thus far, it has been considered that the intelligent vehicle can adapt its driving behaviour without regard to any other conditions. This assumption neglects conditions enforced by both the infrastructure and other ‘un-intelligent’ vehicles on the road. Hence in the next section, the allowable intelligent vehicle speed will be constrained to enforce conditions imposed by the surrounding traffic, and the subsequent effects on the fuel economy over the same urban drive cycles assessed.

4. Implication of restricting relative position of the intelligent vehicle

While significant improvements in fuel economy through the use of feedforward information about traffic conditions supplied by a sensor network were observed in the previous section, it is unlikely that there would be a quantum shift to this technology by all road users. To gauge the impact of the technology using low levels of consumer uptake, it is necessary to remove the assumption that the intelligent vehicle’s velocity (and position) can be assigned irrespective of the traffic flow in which it operates. For example, the adapted velocity profiles obtained using the velocity modification algorithm of the previous section demonstrate a phase lead at certain points in time (for example the first 20 s of all the drive cycles in Fig. 6). This indicates the intelligent vehicle starts moving before it would have if no preview information were available.

Naturally, there will be some cases whereby this situation is not feasible, one example is a traffic signal enforcing vehicle stationarity, and hence it is important to reflect this by applying constraints to the velocity algorithm. The constraint applied in this section is that the intelligent vehicle cannot overtake the position it would occupy on the road if it were traveling without any preview information, i.e. it cannot overtake the un-intelligent vehicle position, or equivalently an unintelligent vehicle directly in front of the intelligent vehicle and traveling at a velocity indicated by the drive cycle. This constraint has been enforced by adjusting the intelligent vehicle's velocity determination algorithm described in the previous section to the one described below.

Intelligent Vehicle Velocity Modification Algorithm (overtaking disallowed)

Step 1: Find position trajectory of the vehicle in front of (leading) the intelligent vehicle over the preview duration, i.e.

$$\hat{x}_{\text{lead}}(t+i\Delta) = x_{\text{lead}}(t) + \alpha\sum_{k=0}^{i} v_{\text{lead}}(t+i\Delta)\Delta \quad \text{for } i = 1,\ldots,\frac{T_{\text{p}}}{\Delta} \tag{3}$$

Note that the sampling period Δ is assumed constant, but Eq. (3) is readily adapted to non-uniform sampling.

Step 2: Set iteration number, j to zero.

Step 3: Find the candidate constant velocity over the next $T_{\text{p}} - j$ seconds, such that the positions of the intelligent and leading vehicle are equal, i.e. $\hat{x}_{\text{int}}(t+T_{\text{p}}-j\Delta) = \hat{x}_{\text{lead}}(t+T_{\text{p}}-j\Delta)$. This candidate velocity is calculated according to:

$$\bar{v}^{j}_{\text{int}} = \frac{\hat{x}_{\text{lead}}(t+T_{\text{p}}-j\Delta) - x_{\text{int}}(t)}{\alpha(T_{\text{p}}-j\Delta)} \tag{4}$$

Step 4: Develop a trajectory for the intelligent vehicle based on $\bar{v}^{j}_{\text{int}}$ over the interval from the current time to $T_p - j\Delta$, i.e.

$$\hat{x}_{\text{int}}(t+i\Delta) = x_{\text{int}}(t) + i\Delta\alpha\bar{v}^{j}_{\text{int}} \quad \text{for } i\Delta = \Delta,\ldots,T_{\text{p}}-j\Delta \tag{5}$$

Step 5: Test whether the predicted intelligent vehicle trajectory overtakes the predicted 'lead' vehicle trajectory, and if necessary update the candidate constant velocity to avoid overtaking, i.e.

- If $\hat{x}_{\text{lead}}(t+i\Delta) > \hat{x}_{\text{int}}(t+i\Delta)$for $i\Delta = \Delta,\ldots,T_{\text{p}}-j\Delta$ then use $\bar{v}^{j}_{\text{int}}$ as the intelligent vehicle's velocity at time t.
- Otherwise, if $\hat{x}_{\text{lead}}(t+i\Delta) \leqslant \hat{x}_{\text{int}}(t+i\Delta)$ for at least one value of $i\Delta$, then increment j and return to Step 3.

The position trajectories calculated for an un-intelligent vehicle, an intelligent vehicle with velocity modified according to the first algorithm (which allows overtaking) and for the new algorithm (which prevents overtaking) are illustrated over a section of a drive cycle in Fig. 8. It is clear that when the lead vehicle is stationary (between 6 and 19 s), the constrained solution results in a slower velocity over the period up to 20 s to ensure that the no-overtaking constraint is not violated. In Fig. 9, the full Australian urban drive cycle is subjected to modified algorithm.

In Fig. 10, the position relative to the lead vehicle is compared over the entire Australian Urban drive cycle for each of the two proposed algorithms. From this figure, it is clear that the maximum separation occurs when the vehicle speeds are highest, and that by preventing overtaking the maximum distance between an intelligent and un-intelligent vehicle is close to 400 m. In Fig. 11, the average and maximum gaps between an intelligent and un-intelligent vehicle are plotted as a function of preview information for each of the three drive cycles used in this study. It can be seen that the unconstrained intelligent vehicle would (on average) tend to lead the un-intelligent vehicle. Preventing overtaking would result in an average separation that grows monotonically with traffic preview. The maximum separation between an intelligent and unintelligent vehicle is also seen to grow monotonically with traffic preview. While the benefits of improved fuel economy also increase, the consumer acceptance of (or resistance to) increasingly large gaps in the traffic flow is likely to

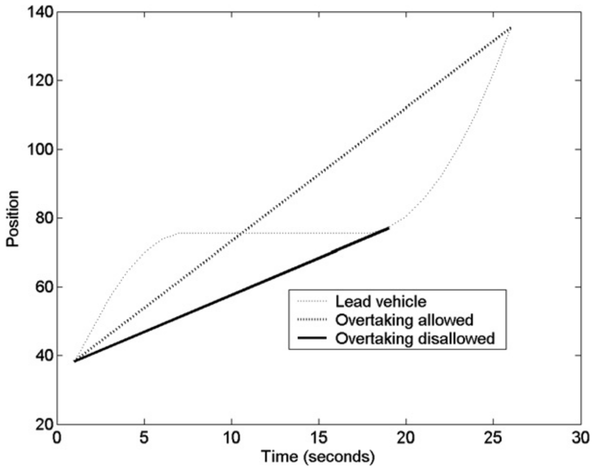

Fig. 8. Position projections for the lead vehicle and the intelligent vehicle with overtaking of the lead vehicle allowed and disallowed. A traffic preview of 25 s has been used in both intelligent vehicle algorithms.

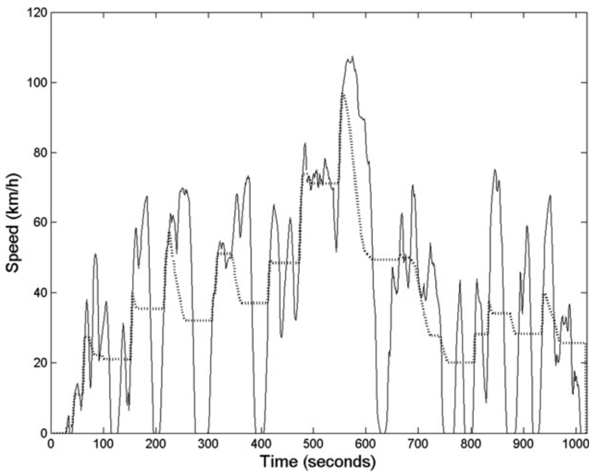

Fig. 9. Australian urban velocity profile (solid) and modified using a traffic preview of 50 s while preventing overtaking (dotted).

limit the effectiveness of extended traffic previews. It would be relatively straightforward to limit the maximum distance between vehicles by imposing a further constraint in the IVVM algorithm, although this would result in some deterioration in achievable fuel economy.

In Fig. 12, the effect on fuel economy of preventing overtaking is assessed for each of the three drive cycles. It is observed that there is only small degradation in performance for the most part, although the achievable modifications under an EUDC-ECE type traffic flow is limited by preventing overtaking and subsequently no further improvement is observed for traffic previews above 80 s. Thus Figs. 11 and 12 present a (not unexpected) conflict – as fuel economy improves, the maximum gap between an intelligent vehicle and an unintelligent vehicle increases thereby testing driver acceptance.

5. Hybrid vehicle equipped with telematics

As a final point of interest, rather than contrasting the performance that can be achieved through the two different technologies, this section deals with the achievable fuel economies if the technologies are combined to

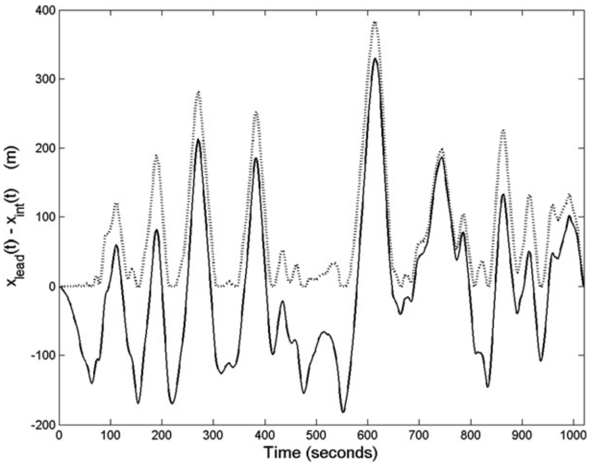

Fig. 10. Comparison of position of intelligent vehicle relative to a vehicle following drive cycle when overtaking is allowed (solid) and disallowed (dotted).

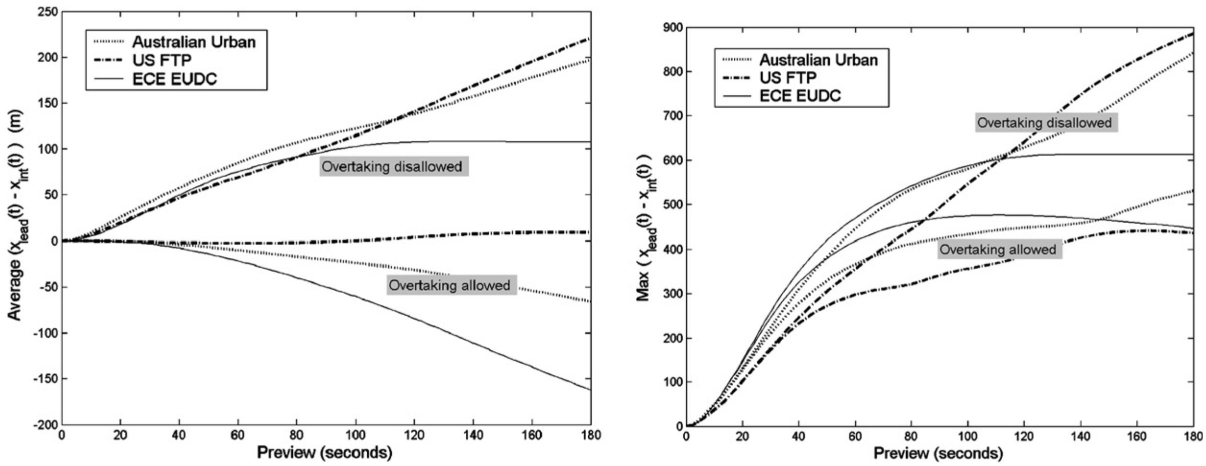

Fig. 11. (Left) Average and (Right) maximum distance separation between the intelligent vehicle and the vehicle leading it, for overtaking allowed and disallowed.

produce an 'intelligent hybrid' – i.e. a vehicle with a hybrid drivetrain that is equipped with telematics enabling some feedforward information about speed trajectories to be obtained. In order to enforce a change in the state of charge of less than 0.5% between the start and end of the drive cycle, the default hybrid control strategy used and the initial state of charge varied until the constraint was met. The resulting fuel economy for the intelligent hybrid using both intelligent vehicle velocity modification algorithms (overtaking allowed and not allowed) over each of the three drive cycles are illustrated in Fig. 13.

From the plots shown in Fig. 13, only limited conclusions can be drawn. Firstly, it is noted that there is a general trend in decreasing fuel use with increasing information seen for all three drive cycles. However, this decrease in fuel use is non-monotonic, and this non-monotonicity is due to several factors. The primary one is that the optimum fuel use will not depend solely on minimizing the vehicle speed deviations, since decelerations are required to use regenerative braking. This is why hybrid vehicles are significantly better then conventional drivetrains in terms of fuel economy during urban drive cycles, but the level of improvement decreases during highway driving. Furthermore, the minimization of fuel also depends on the individual efficiency maps

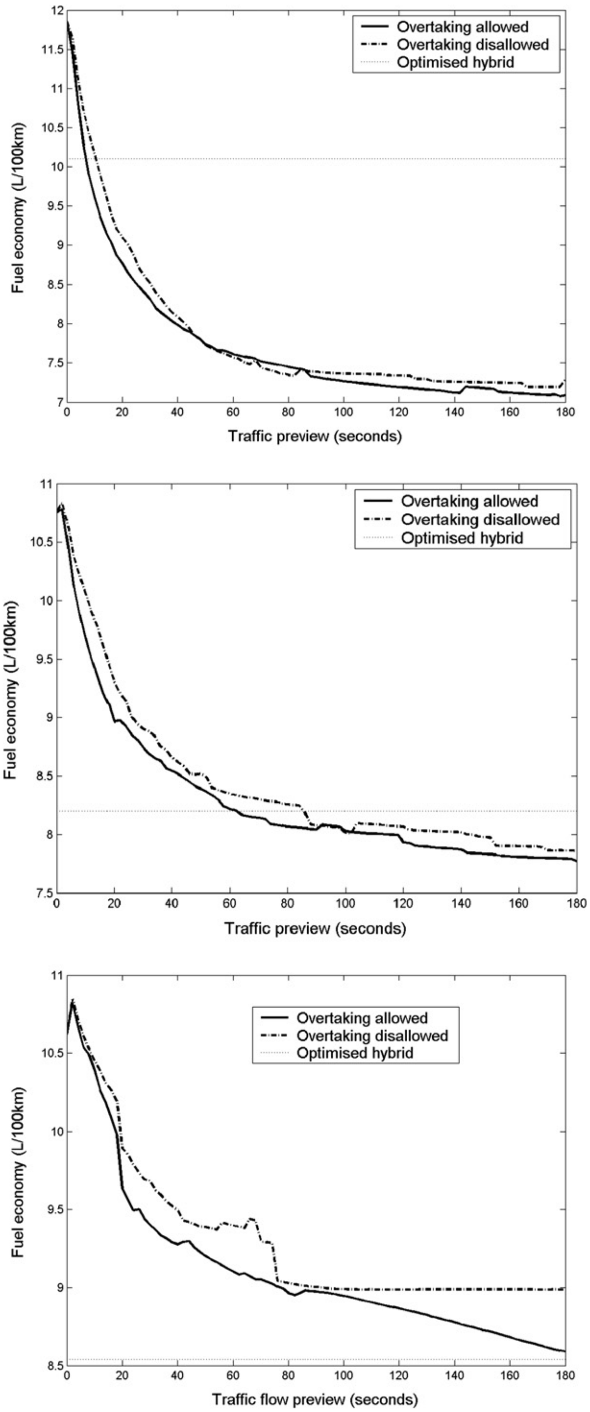

Fig. 12. Fuel economy as a function of preview information with overtaking allowed and disallowed using the Australian urban cycle (top left) US FTP cycle (top right) and ECE-EUDC cycle (bottom). For reference optimized hybrid fuel economy is also included in each plot.

of the internal combustion engine and electric motor, as well as the switching strategy of the hybrid controller. A dynamic programming optimization approach over an entire drive cycle has been used to derive the optimal switching strategy when the vehicle speed is fixed to the drive cycle in Kirschbaum et al. (2002), however the

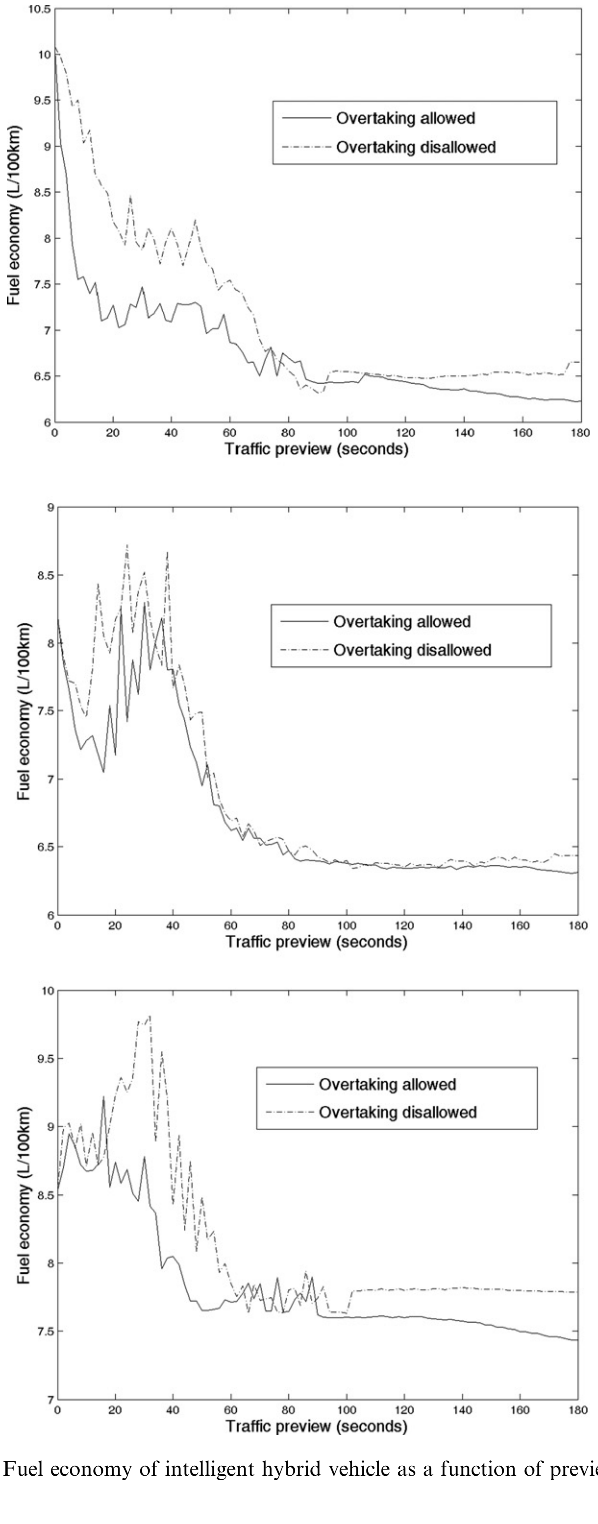

Fig. 13. Fuel economy of intelligent hybrid vehicle as a function of preview time.

optimal use of limited traffic preview information in an online controller remains an open problem, particularly if vehicle speed is allowed to vary away from the traffic flow. If a variable vehicle velocity is added as a dimension to the constrained problem the solution is certainly non-trivial and requires further research effort.

6. Conclusions

This paper presents a comparison between two of the emerging technologies in automotive systems, hybrid drivetrains and telematics capability. Following the development of an optimal hybrid configuration that matches the performance of the baseline test vehicle, it was found through simulation that the fuel economy improvements possible through optimal hybridization ranged between 15% and 25% relative to the baseline vehicle over three standard urban drive cycles.

The test vehicle was then equipped with telematic capability, and an algorithm proposed that made use of preview information provided by the telematics to determining the vehicle's modified speed at each point of the drive-cycle. It was observed that the same fuel economy as recorded for the hybrid drive cycle could be achieved with less than 60 s preview information on two realistic drive cycles. Further traffic flow information up to 180 s resulted in as much as 33% fuel economy improvements relative to the original test vehicle.

The proposed algorithm was then constrained to prevent overtaking of any part of the traffic flow. It was found that the fuel economy was only slightly worse than for the unconstrained case, and again matched the hybrid fuel economy with relatively short preview information. The potential gaps in traffic that would result from the use of both proposed algorithms was also investigated. This highlighted the trade-off between intermittent positional gaps to an un-intelligent car immediately in front of the intelligent vehicle and fuel economy improvement.

Finally, the two technologies (hybrid and telematics) were combined in one vehicle to create an 'intelligent hybrid' vehicle. While there were general trends indicating improvement in fuel economy with traffic preview, the multi-dimensional nature of the problem (current vehicle speed, power split between the electric motor and internal combustion engine and battery state of charge must all be considered) ensures that the optimal use of the feedforward information, particularly for short traffic previews, remains an ongoing research problem.

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