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Fuel Economy Benefits of Look-ahead Capability in a Mild Hybrid Configuration

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Abstract: Mild hybrid electric vehicles (HEVs) take some benefits of full HEVs while having lower initial cost and weight, making them a more viable proposition for OEMs looking to enter the hybrid market. The popularization of mild hybrid electric vehicles (HEV) has exposed a new research potential in hybrid energy management. The optimal control of fuel economy in such a configuration is hard to achieve due to its multi-dimensional nature and the absence of future information. The blossoming telematics industry offers the potential to gather future information at relatively low cost through on-board sensing and vehicle-to-vehicle communication systems. In this paper, a novel approach to further fuel consumption minimization of a mild HEV is proposed. The approach is focused on adjusting the by-wire throttle in the vehicle in order to modify forward velocity, as well as controlling the power split between two sources. We show that on a realistic urban drive cycle, the telematic-enabled mild hybrid vehicle with preview of 150 meters can achieve up to 20% fuel saving compared to a comparable baseline conventional powertrain vehicle, and a further 1% fuel saving relative to previously published algorithms. The potential for further improvement in fuel economy through optimizing the use of the electric motor is also discussed.

Keywords: Hybrid vehicle control, Intelligent vehicle, Telematics

1. INTRODUCTION

Although a full hybrid electric vehicle (HEV) offers superior fuel economy, the high initial cost, mechanical complexity and increased weight still remain as significant obstacles for OEMs to replace conventional powertrain vehicles. In order to facilitate the transition towards hybrid configurations, many OEMs are currently adopting vehicles with a mild hybrid configuration in their fleets – i.e. these are conventional sized internal combustion engines coupled with an electric motor of up to 15kW. The additional cost of the electric motor is offset by the removal of the starter motor and alternator from the vehicle, while retaining the larger internal combustion engine does not require significant changes to existing manufacturing lines. Furthermore, consumer demand for large sedans and sports utility vehicles in non-European markets remains high, thereby favouring configurations with larger internal combustion engines.

Since the electric motor size in the mild hybrid is smaller than in the full hybrid configuration, it cannot be used as widely through the drive cycle. Typically, in a mild hybrid configuration the electric motor is used only for starting, to enable engine shut-off when the vehicle is stationary, and for some small power assist. There is clearly a relative reduction in motor utility compared to a full hybrid, however fuel savings of the order of 10-15% may be observed relative to a non-hybrid vehicle. GM claims that by implementing a simple mild hybrid system on the 2007 model Silverado can achieve overall fuel saving of 12%.

A range of power management strategies for full hybrid vehicles has been discussed in the literature. Earlier approaches involved heuristic control strategies such as the rule-based (Jalil, 1997) or fuzzy logic (Schouten, 2002) approaches that utilise high low-speed torque characteristic of the electric motor. These approaches helped enable early hybrid implementations, however did not make full use of the potential fuel savings available.

As an alternative, model-based control methods have been suggested because rule-based approaches do not optimally consume fuel. Dynamic programming approaches (Brahma, 2000), (Back, 2002) solved for the global optimal power split strategy over an entire drive cycle. While useful in identifying the global optimum, these approaches are not suited to real time implementation as they require knowledge of the full drive behaviour before the trip, which is clearly infeasible.

More recent approaches have focussed on the problem of real time applicability of the algorithm by approximating the complete optimal problem. One approach that improves practicality is centred on calculating the equivalent fuel consumption of the battery at all points in time and consequently allows the fuel and electrical energy to be combined in a single cost. This cost is then minimised instantaneously at each operating point using what is termed in (Paganelli, 2002) as an Equivalent Consumption Minimisation Strategy (ECMS).

The ability of ECMS to cope with unforeseen future driving behaviour was further improved by Sciarretta *et al.* (Sciarretta, 2004). In this work the authors introduced probability factors to the equivalence factor to account for the future charging/discharging behaviour of the electrical energy. This instantaneous optimisation strategy can be applied online but has weakness in reflecting the fuel-electric dependency at each operating point of the engine and motor because it assumes the linear equivalency of the fuel and electric energy obtained by averaging over the whole known drive cycle.

The limitations of the control strategies in the absence of future information about the traffic behaviour can be overcome with use of on-board telematics (Sciarretta, 2007), (Manzie, 2007). This is becoming more feasible as more vehicles become equipped with radar based systems which have a range of up to 150m (Rasshofer, 2005). Further range improvements are steadily hitting the market, with the latest vehicle sensor from Ibeo offering a range of up to 200m. Naturally, vehicle to vehicle communication systems offer even greater potential feedforward information and have become readily affordable over the past decade.

The aforementioned work has focussed on adjusting the hybrid power split to optimise fuel economy, however in (Manzie, 2007) it was demonstrated that adjusting the vehicle velocity subject to feedforward information can also substantially improve fuel economy of a *conventional* powertrain vehicle. In that work, the authors demonstrated that averaging the vehicle velocity over a feedforward window is a useful approach for the conventional vehicle, where eliminating acceleration and decelerations is beneficial. This approach did not alter arrival time and velocity modifications were constrained by the positions of other vehicles on the road. However, while the algorithm worked well with conventional powertrain vehicles, the solution was shown to be sub-optimal for the case of HEV due to the increased dimensionality of the problem: e.g. some deceleration of the vehicle can actually be beneficial to regenerative braking. Furthermore, the approach uses telemetry information given in a fixed preview time, whereas the telemetry in practice is likely to be restricted by the range in distance.

The work outlined in this paper extends the prior work in a number of ways. Firstly, the telemetry information is specified in units of distance rather than time, thereby better establishing allowing the effectiveness of different range telematic systems. Secondly, the velocity modification algorithm is slightly modified for use with a mild hybrid configuration, and finally the integration with state-of-the-art power switching algorithms is discussed.

The layout of the paper is as follows: in Section 2 the virtual vehicle and drive cycle of interest are introduced, while in Section 3 minor changes are made to the velocity modification algorithm. In Section 4, a new velocity modification algorithm is discussed. In Section 5, potential for combining existing power split strategy to the algorithm is studied. Conclusions and future work are considered in Section 6.

2. SIMULATION ENVIRONMENT

To obtain all measures of fuel efficiency in this work, it was necessary to simulate various drivetrains. The software package used for the simulations is ADVISOR (Wikpe, 1999), which has been adopted by many researchers and is accepted to provide very good trends in fuel economy over a wide class of vehicles including hybrid and conventional powertrains. ADVISOR calculates fuel economy by a reverse process starting from the drive cycle - i.e. for a given drive cycle, the torque and power requirements at the wheel at a particular instance are back calculated to the fuel converter through the dynamics of other components, and the total fuel consumption is obtained using engine maps obtained from dynamometer-based testing.

The following sections outline the vehicle model and drive cycle used in this study.

2.1 Conventional Vehicle Model

A full sized conventional vehicle is used as the baseline for comparison in terms of fuel economy. The specification of this vehicle is chosen to meet that of the family size sedan, which occupies approximately 30% of the total vehicle sales in Australia each year. The key characteristics of the conventional vehicle of interest are outlined in Table 1.

Table 1. Conventional Vehicle Model Characteristics

Total weight	1642 kg
Chassis weight	1000 kg
Coefficient of drag	0.366
Transmission	Manual, 5 speed
Transmission efficiency	95%
Gear ratios	3.5 : 2.14 : 1.39 : 1 : 0.78
Max. power output	168 kW

Fuel use and power maps for this vehicle were obtained through extensive engine dynamometer testing, while vehicle parameters such as coefficient of drag and tyre rolling resistance were supplied by the manufacturer and are given in (Manzie, 2007).

2.2 Mild Hybrid Vehicle Model

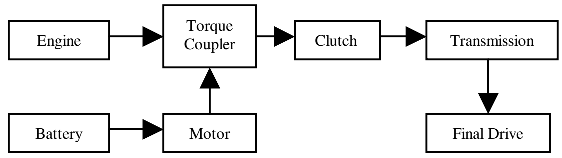

Figure 1. Parallel Starter/Alternator drivetrain block diagram

It was necessary to develop the models for a mild hybrid vehicle based on industry trends as no equivalent mild hybrid is currently in production. The size of the electric motor in the mild hybrid vehicle model was set to 15 kW, based on the fact that vehicles recognised as mild hybrids on the current market employ motors ranging from 11-15 kW. The combustion engine is downsized by the same amount to keep the total peak power available equal to that of the conventional vehicle model, thereby allowing similar performance characteristics and a 'fair' comparison in both cases. The underlying assumptions behind the use of the electric motor in the mild hybrid vehicle are:

- the vehicle supports regenerative braking
- the engine shuts off when the vehicle is stationary

The drivetrain configuration in Figure 1 is adopted for modelling the mild hybrid vehicle. The clutch is set to be engaged while the torque required from the engine is negative, to allow the negative torque from the wheel to be transmitted up to the motor for regenerative braking. The ratio between regenerative braking and friction braking at different vehicle speeds adopted in simulation is the default value in the software. From simulations, it is observed the efficiency of the regenerative braking in the model is 62.5% on average, taking account of the loss through other vehicle components.

2.3 Drive Cycle

The drive cycle used for the simulation is the Australian Urban Cycle, which was developed based on extensive logging of urban driving in passenger vehicles (Watson, 1982). Although the European Drive Cycle is widely used for certification purposes, the geometrical nature of the cycle is not representative of real world driving and is not considered useful to this study, where the focus is on potential real world fuel economy.

The Australian Urban Cycle is illustrated in Figure 2 as the solid line, and both low-speed, start-stop and high-speed behaviour are observed to be present.

3. VELOCITY MODIFICATION WITH DISTANCE PREVIEW

The Intelligent Vehicle Velocity Modification (IVVM) algorithm of (Manzie, 2007) was modified to have fixed traffic preview in distance rather than time. Then this algorithm was used to compute the velocity of an intelligent vehicle over the Australian Urban Cycle with 400m previews. The profiles before and after velocity modification are shown in Figure 2.

The key characteristic is the intelligent vehicle avoids a complete stop when possible by decelerating before the leading traffic starts to decelerate. This behaviour increases the distance separation between the intelligent vehicle and the lead vehicle. The intelligent vehicle then schedules its speed such that it travels at a constant speed over the distance separation and merges back smoothly with the accelerating traffic ahead. The optimality of this approach under certain limiting assumptions was shown in Section 8.4 of (Guzzella, 2005).

Altering the previewed distance induces the variation in the time the intelligent vehicle start to decelerate, as well as the duration of the constant speed cruise. The change in the fuel economies for the conventional vehicle and the mild HEV for varying look-ahead distance are plotted in Figure 3 and a numerical comparison is in Table 2.

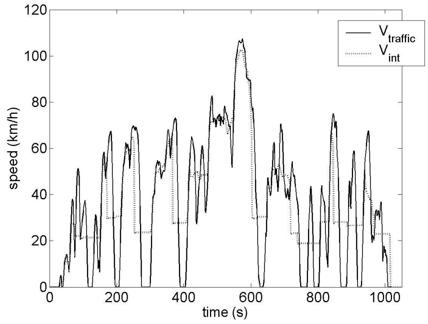

Figure 2. Velocity profile of a conventional vehicle with IVVM run on the Australian urban cycle

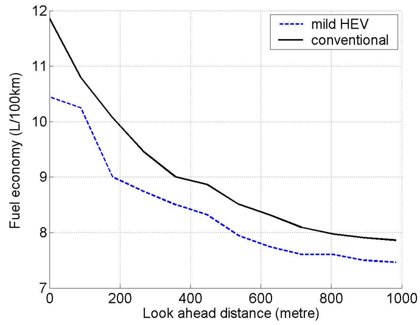

Figure 3. Fuel economy as a function of preview distance for conventional and mild hybrid vehicles

Table 2. Summary of fuel consumption

Vehicle Type	Preview (m)	Equivalent Fuel Consumption (L/100km)	Improvement relative to conv. vehicle
Conventional	0	11.82	--
	150	10.24	13.4%
	800	8.05	31.9%
Mild HEV	0	10.41	11.9%
	150	9.50	19.6%
	800	7.65	35.3%

The first important point to note is that without any velocity modification, the mild hybrid has approximately 12% improvement in fuel economy relative to the conventional vehicle, which is consistent with industry reports.

Secondly, as the traffic preview increases, both vehicles exhibit significant improvements in fuel economy, with the mild hybrid maintaining an advantage of between 0.5-1 litre/100km in fuel efficiency, which is principally due to engine shut off. As shown in Table 2, over 35% fuel saving is achievable for mild hybrids with 800m traffic preview, although this preview is not supported by state of the art vehicle sensors. The continual improvement in fuel efficiency with preview distance provides good motivation for further iterations of the velocity modification algorithm.

Non-monotonic decrease in the fuel economy of the full hybrid vehicle with increasing look-ahead was reported in (Manzie, 2007), but is not observed for the mild hybrid in Figure 3. This is likely to be due to the smaller utility of the electric motor in a mild hybrid configuration, and raises the possibility that the complexity of the full hybrid optimisation problem (where vehicle velocity and power split have a continuum of solutions in an allowable range) may be more easily addressed in a mild hybrid vehicle (due to a vast reduction in the search space required of the optimisation algorithm).

4. RANGE BASED VELOCITY MODIFICATION ALGORITHM

As mentioned in the introduction, travelling at a constant speed, hence reducing the frequency of acceleration and deceleration, does not necessarily guarantee the minimal use of fuel for of hybrid vehicles. This is reflected by the result that the percentage improvement in fuel economy by adopting hybrid configurations for highway cycles is significantly less than for city driving. An optimal solution would result from an algorithm considering all factors of influence – not only the vehicle's velocity but the optimal power split which is dependant on the battery state of charge (SOC) and use of regenerative braking.

As a interim step, we will first consider the fuel economy improvements possible through velocity modification only, through some modifications to the IVVM algorithm from (Manzie, 2007). A heuristic control of power split is considered in this first instance only. The potential to include a more intelligent control approach will be considered Section 5.

4.1 Formulation of the RBVM

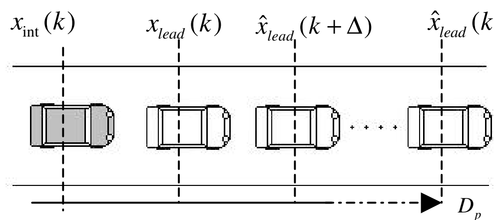

Figure 4. Schematic of traffic preview

The key component of the Range Based Velocity Management (RBVM) algorithm is the vehicle is considered to be a discrete particle in a traffic flow, and has information based on telemetry feedback about all other vehicles within the range of it's onboard telemetry system. For the purposes of this work, the current vehicle (whose velocity profile may be adjusted) is termed an 'intelligent' vehicle, while the vehicle immediately in front of the intelligent vehicle is termed the 'lead' vehicle. For simplicity, all overtaking is prevented, i.e. intelligent vehicle cannot go past the lead vehicle or be overtaken by any followers. Consequently, only the relative position/lag of the lead and intelligent vehicle in the traffic stream is modified.

A schematic of the situation is shown in Figure 4. The dark vehicle represents the intelligent vehicles position at time k, while the current position of the lead vehicle and the predicted future positions are also shown. An alternative graphical representation of is shown in Figure 5, where the dotted line represents the position of the lead vehicle as a function of time, while the solid lines represent possible velocity trajectories of the intelligent vehicle in the preview distance.

While the IVVM algorithm of (Manzie, 2007) proposed constant velocity throughout the feedforward range (shown as a grey line in Figure 5), the RVBM attempts to incorporate possible decelerations by allowing two vehicle velocities in the same range. Two possible trajectories are labelled v_1 and v_2 in Figure 4. The two trajectories simulate the intelligent vehicle approaching the front vehicle faster for the first half of the preview, and decelerate in the second half. The aim of this is to induce the deceleration behaviour of the intelligent vehicle rather than travelling at constant speed to collect energy through regenerative braking. This approach is devised from the idea of dynamic programming over the distance previewed, simplified through intuitive constraints on velocity (e.g. going backwards) and with two large time grid for the fast computation. Each trajectory is simulated through the ADVISOR model and the one with the lowest fuel use (subject to possible state of charge constraints) is adopted. The procedure is repeated every time new information becomes available.

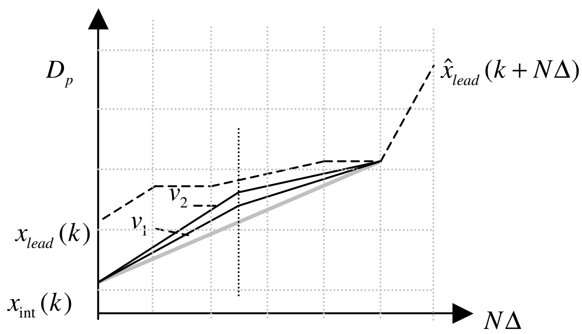

Figure 5. Graphical representation of RBVM algorithm

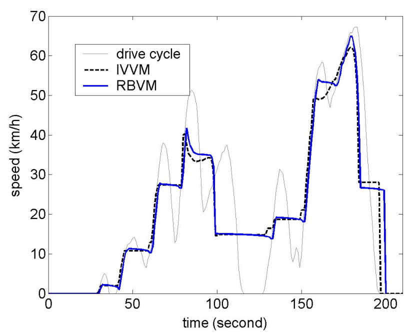

Figure 6. Modified velocity profiles using the IVVM and RBVM algorithms for the first 200 seconds of the Australian Urban Cycle. In both cases 150 metre traffic preview is used.

4.2 RVBM Simulation Results

The improved algorithm shows a slightly different characteristic in velocity management in comparison with the original IVVM algorithm. The results from the two methods are plotted in Figure 6 over a subset of the Australian Urban cycle. The constant speed regions in IVVM are replaced by a steady decrease in velocity in RBVM, which allow regenerative braking to capture energy in this deceleration phase. On the other hand, the peak velocity is increased due to initial speed up.

Table 3 presents a numerical comparison of the mild HEV using IVVM and RBVM over the Australian Urban Cycle. The result shows that the RBVM algorithm further reduced the fuel consumption by 0.5% with 150 metres of traffic preview. This improvement, while minor, indicates that there is potential for improvement, particularly in combination with other power split strategies.

Table 3. Mild hybrid vehicle run on Australian Urban Cycle

Vehicle Type	Preview (m)	Equivalent Fuel Consumption (L/100km)	Improvement relative to a mild hybrid
Mild HEV	0	10.41	--
Mild HEV IVVM	150	9.50	8.7%
Mild HEV RBVM	150	9.45	9.2%

5. VELOCITY MODIFICATION WITH IMPROVED HYBRID POWER SPLIT ALGORITHM

The default torque split controller in ADVISOR is a rule-based controller, which is one of the earliest control approaches. To investigate a further potential fuel saving on a telematic enabled HEV, the idea of ECMS from (Sciaretta, 2004) is implemented together with the RBVM algorithm. Firstly fuel equivalence of the electrical energy use is evaluated through the Australian Urban Cycle, as shown in Figure 7.

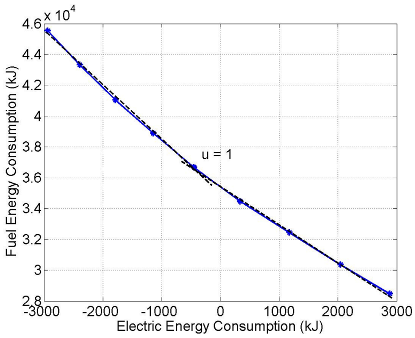

Figure 7. Fuel and electric energy dependency

Two piecewise linear curves indicate the difference between the charging and discharging efficiencies of the battery. The linear relationship also exists between the litres of fuel used and the change in SOC. This relationship is used to convert the SOC deviation at the end of the cycle from the initial state to penalise the final fuel consumption. The control input is the torque split ratio u which is defined by:

$$u = \tau_{engine} / \tau_{torque\_coupler}$$

When the torque required at the torque coupler is solely supplied by the engine, $u = 1$. Choice of u at each instance is restricted by the specification of the electric motor chosen due to its limited small maximum power output. The cost function for evaluating the equivalent fuel consumption at particular velocity choice and torque split ratio is:

$$J = \Delta E_{fuel}(t,u) + s\Delta E_{electric}(t,u)$$

where s is the equivalence factor derived from the gradient of Figure 7. The simulation for RBVM algorithm with ECMS is run through Australian Urban Cycle with 0.01 increments for torque split ratio.

The power output from the engine using RBVM algorithm with the default rule-based controller and RBVM with ECMS through a section of a drive cycle are plotted together in Figure 8. ECMS controller requests less power from the engine and favours the use of electric energy. The performance of the proposed method is summarised in Table 4 together with the result from previous sections of this paper. Firstly the simulations are run with 150m preview, and then with 400m preview to assess further potential with improving sensor technology in near future.

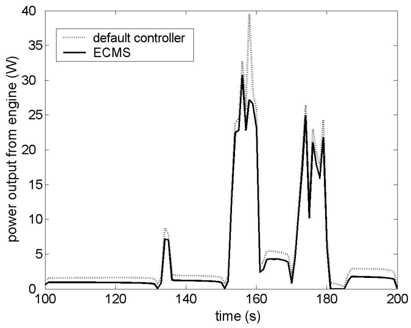

Figure 8. Comparison of power output from engine between default controller (dotted) and using ECMS (solid)

Table 4. Comparison chart for all vehicles tested through Australian Urban Cycle

Vehicle Type	Preview (m)	Equivalent Fuel Consumption (L/100km)	Improvement relative to conv. vehicle
Conventional	0	11.82	--
Mild HEV	0	10.41	11.9%
Mild HEV IVVM	150	9.50	19.6%
Mild HEV RBVM	150	9.45	20.0%
Mild HEV RBVM +ECMS	150	9.41	20.4%
Mild HEV IVVM	400	8.46	28.4%
Mild HEV RBVM	400	8.39	29.0%
Mild HEV RBVM +ECMS	400	8.35	29.4%
Full HEV (Manzie, 2007)	0	10.10	14.6%

Not surprisingly, there is improvement in fuel economy as the velocity modification algorithm increases in complexity and more feedforward information is available. When 150m preview is used, it is important to note that the total maximum improvement shown is of the order of 20%, with contributions from the mild hybridisation and the velocity modification being almost equal. When the preview length is increased to 400m, the observed improvement due to velocity modification almost doubles.

Compared to the full HEV model from (Manzie, 2007) a mild HEV using ECMS and 150m and 400m telemetry can achieve 6% and 15% fuel saving respectively. These results include driving in both urban and highway modes, and may not encapsulate the full benefits of mild hybrid in urban settings. Consequently, further analysis on the proposed algorithms was completed on the first 200 seconds of Australian Urban Cycle with 150m preview to emphasize the city-driving pattern within 60km/h range. The results are summarised in Table 5.

Table 5. Comparison chart for all vehicles tested through the first 200 seconds of Australian Urban Cycle

Vehicle Type	Preview (m)	Equivalent Fuel Consumption (L/100km)	Improvement relative to conv. vehicle
Conventional	0	17.00	--
Mild HEV	0	14.42	15.2%
Mild HEV IVVM	150	12.92	24.0%
Mild HEV RBVM	150	12.74	25.1%
Mild HEV RBVM +ECMS	150	12.39	27.1%

Table 5 reflects the strength of mild hybrids in city driving conditions against the conventional vehicle. Moreover other proposed algorithms also show a distinct improvement in fuel consumption compared to the simulation over the whole Australian Urban Cycle. Incorporating ECMS can further improve 2% fuel saving on top of RBVM algorithm. However, compared to the result from (Sciaretta, 2004) this improvement is minimal. The reason behind this is that, a small motor in a mild hybrid has a narrow margin of power output where full hybrids have the electric motor equally capable of delivering high power as the engine. The performance of the RBVM algorithm with ECMS is to be tested on a full hybrid vehicle model where torque assist by the electric motor is more frequent during the cycle.

6. CONCLUSIONS

This paper compares two velocity modification algorithms, previously published IVVM, which is non-model-based, against the new RBVM algorithm which finds optimal velocity based on a mild HEV model which supports regenerative braking. The proposed algorithm can enhance the fuel economy of mild HEVs and it is shown to be most effective at low speed ranges. Although the additional saving is only 1% relative to the original IVVM, incorporating an ECMS torque split strategy can result in another 2% saving in city driving condition. The algorithm is to be further explored on a full HEV, to investigate its potential with a larger electric motor. The work is to be extended for a global optimisation using dynamic programming with a fixed telematic preview of the traffic, with a view to finding the best subset of velocity profiles to test over the preview distance for use in a RBVM-like approach. Furthermore, hardware-in-the-loop testing is planned in near future for 'real-world' validation of the algorithm. Other possible extension to this work is the information fusion of multiple vehicle sensors, e.g. combining vehicle-to-vehicle communication with GPS and radar telemetry, which would allow a longer look-ahead of the traffic with current limited sensor technology.

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