Real-time predictive eco-driving assistance considering road geometry and long-range radar measurements

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Abstract
Eco-driving assistance systems incorporating predictive or feedforward information are a promising technique to increase energy-efficiency and reduce CO2 emissions from road transportation. This work gives details of such a system that was recently developed by the authors, which uses real-time data from GPS and automotive radar to perform a predictive optimisation of a vehicle’s speed profile and coaches a driver into fuel-saving and CO2-reducing behaviour. A repeated-measures study carried out in a fixed-base driving simulator indicated an overall reduction in fuel consumption of 6.09%, which was significantly greater than improvements expected from reductions in average speed. Adjusted for average speed, fuel-efficiency improvements when using the system are similar to those observed in unassisted eco-driving, but with improvements in travel time in motorway situations. Finally, an on-road prototype is described in which the optimisation is solved using data from vehicle sensors, successfully demonstrating that real-time implementation of the system is feasible.

1 INTRODUCTION
Since 1990, significant progress has been made on decarbonisation of economies within the European Union (EU), with total EU carbon dioxide (CO2) emissions 23.5% lower in 2017 than they were in 1990 [1]. While emissions from sectors such as electricity production, agriculture and industry have decreased significantly from 1990 levels (by 29.9%, 19.2%, and 36.7%, respectively), emissions from road transport have increased by 22.8% in the same period. As a sector, road transport accounts for 20.7% of total CO2 emissions across the EU, so significant reductions in road transport emissions are needed to meet future decarbonisation targets.

Eco-driving is the reduction of fuel usage of a road vehicle by driving it in an energy-efficient way, and has been described as a “low-hanging fruit” that can provide a 5–10% reduction in fuel usage and resulting CO2 emissions without requiring changes to existing vehicle drivetrains [2]. This requires driving behaviours such as gentle acceleration, avoiding braking by anticipating traffic flow and early upshifting of gears in cars with manual transmissions. These changes in behaviour may be achieved either by driver training, or by incorporating driver assistance devices into the vehicle [3]. Many such devices have been suggested ranging from simple displays that give feedback to the driver about their fuel economy, to more sophisticated haptic and combined auditory-visual interfaces [4]. Further innovations include the incorporation of feedback on drivers’ past actions and feedforward advice to make context-dependent recommendations, but as yet most such devices are unable to detect the presence of a vehicle ahead [5]. As well as improving fuel efficiency beyond that achievable by drivers alone, these assistance systems can induce learning effects in drivers to further promote more economical driving [6]. This is particularly promising for long-term CO2 reduction efforts, as eco-driving behaviours are reported as...
easy to adopt by drivers [7], but difficult to maintain long-term without regular feedback as drivers fall back into old habits [8].

Dynamic eco-driving systems, in which advice is communicated to the driver in real-time based on sensor and infrastructure information, are demonstrated to give reductions in fuel consumption of 10–20% in simulation studies of highway driving situations [9], with the greatest reductions occurring in congested traffic. One such system was prototyped within the EU EcoDriver project, with a precise polynomial model of fuel consumption minimised using dynamic programming to develop an optimal speed profile and the resulting algorithm tested on a real vehicle in a restricted test-track situation [10]. These systems are also useful for electric vehicles where they can be used to extend the possible driving range [11]. Pre-computed optimal speed profiles can be displayed to the driver via the speedometer [12]. In surveys of car drivers, eco-driving assistance systems are rated as useful, with drivers welcoming their deployment in general [13]. The sensing, infrastructure communication and optimisation required for such systems may also be useful in adaptive cruise control applications designed to reduce fuel usage [14].

In determining the eco-driving behaviour suitable for a given driving situation, optimal control has been identified as a useful framework, with analytical solutions possible in some simple cases and numerical solution methods being applicable to more general problems [15]. For real-time eco driving assistance, Model Predictive Control (MPC) has been demonstrated in traffic simulations to give fuel-efficiency benefits by solving an optimal control problem that incorporates information on the positions of other vehicles and prediction of the acceleration behaviour of the preceding vehicle based on, for example, traffic signals [16]. More recently researchers have also considered the effect of road curvature on eco-driving solutions [17], accounting for limits on the allowable lateral acceleration in curves. The optimal speed is constant while traversing a circular curve, but varies in a complex way on clothoid curves and on typical roads with transitions between straight, clothoid and circular sections.

A major concern in the development of any eco-driving assistance system is user acceptance [18]. To this end, the system should respect the driver's preferences on relevant quantities such as lateral and longitudinal accelerations, cruising speeds and following distances. The possibility of making driver assistance reflect driver behaviour has already been suggested for adaptive cruise control, in which the system may be trained by drivers to reflect their preferences on speed and following distance [19]. In this context of improving driver assistance by consideration of driver preferences, recent works by the authors have developed parametric models of driver behaviour suitable for safety [20] and eco-driving assistance applications [21]. Having developed this theory, the present work applies a similar model to a prototype eco-driving assistance system.

This paper concerns an eco-driving assistance system recently developed by the authors at the University of Southampton, UK, which accounts for both the motion of the preceding vehicle and upcoming road curvature to suggest actions to the driver that minimise fuel consumption. The fuel-efficient velocity profile is determined by solving a non-linear MPC optimisation numerically in real-time, exploiting measurements from GPS and long-range automotive radar to provide knowledge of upcoming road geometry and traffic. This assistance system has several improvements and innovations compared to those in the existing literature:

- As the system considers both path curvature of the driving route and motion of any leading vehicles, it is general-purpose system suggesting fuel-efficient behaviour in real-time in a variety of scenarios such as urban and rural driving and both high and low traffic densities.
- Driver preferences on longitudinal and lateral acceleration, cruising speed and vehicle spacing are incorporated, such that the system coaches the driver into fuel-efficient behaviour consistent with these preferences.
- The system contains an adjustable trade-off parameter $\alpha$ that can be personalised to either give more emphasis to fuel economy, which requires coasting down and gentle accelerations, or naturalistic driving, which admits higher accelerations and more closely follows driver preferences on speed and following distances.

Considering the specific contributions of this paper, we describe the architecture and development of the system as it was implemented in on-road testing, following a previous conference publication detailing the system as implemented in a driving simulator [22]. We then provide results from a repeated-measures study of 36 participants driving in the simulator, designed to assess reductions in fuel usage as calculated from a detailed quasi-static model of the simulator vehicle powertrain. A repeated-measures ANOVA analysis that includes average speed in each test condition as covariates allows changes in fuel usage to be compared to those that would be expected given any changes in average speed when using the system, so that we can distinguish between reductions in fuel usage caused by participants driving more slowly, and those from other causes such as avoidance of braking. We then describe on-road testing to assess technical feasibility of the system. Applying the system to a real-world vehicle required the development of a suitable fuel consumption model, which was validated using measurements from the vehicle CANbus. Finally, we provide experimental results on the availability and reliability of sensor data and provide qualitative analysis of the system performance in practice.

2 | SYSTEM ARCHITECTURE

Schematically, the system is divided into “Perception,” “Decision,” and “Action” layers as illustrated in Figure 1. The Perception layer consists of a GPS unit, front-mounted doppler radar sensor, and the vehicle ECU which can provide data on vehicle speed, gear, and instantaneous fuel consumption. The Decision layer is a receding-horizon MPC scheme that attempts to minimise a weighted sum of fuel consumption, acceleration, speed and following distance objectives. This is informed by models...
of vehicle fuel consumption, driver preferences, and road curvature which are described in detail in later sections. The action layer consists of a visual human-machine interface (HMI) taking the form of a green and orange “eco-band” overlaid on a vehicle speedometer, inspired by “eco-speedometer” designs rated highly in usefulness and user acceptance in previous studies [18].

Considering the in-vehicle prototype developed by the authors, communication between the Perception and Decision layers occurs over the vehicle CANbus, with the Decision and Action layers implemented on a tablet PC in the vehicle cabin for the on-road prototype, while communication between the Decision and Action layers was implemented using TCP/IP. For simulator testing, the Perception layer was replaced with updates from the simulation software. A PC present in the simulator laboratory was used to run both the simulation software and the Decision layer, with the Action layer on a tablet PC in the vehicle cabin.

3 PERCEPTION LAYER

3.1 GPS-based localisation

To account for upcoming road curvature, the vehicle must be located on an internal map of the route which can be accomplished using GPS measurements of the vehicle’s latitude and longitude. This internal map is specified as a sequence of x-y points representing the route in a local coordinate system, allowing translation of the measured latitude and longitude into a distance x along the route appearing in a curvature function κ(x), which is used in the Decision layer. In the on-road prototype, the vehicle was equipped with a Racelogic VBOX 3i GPS unit and data logger, which outputs data continuously at a rate of 100 Hz to the vehicle CANbus.

Each time an updated latitude-longitude pair is received from the GPS, this is converted to the local coordinate system, denoted as a vector \( \vec{y} \), and the nearest two points on the route, denoted \( \vec{y}_k \) and \( \vec{y}_{k+1} \), are identified. If the distances of \( \vec{y}_k, \vec{y}_{k+1} \) along the route are \( x_k \) and \( x_{k+1} \), respectively, then the current distance x may be approximated by the interpolation:

\[
x = x_k + \sigma (x_{k+1} - x_k),
\]

where \( 0 \leq \sigma < 1 \) measures the progress of the vehicle in travelling from \( y_k \) to \( y_{k+1} \) and may be given by

\[
\sigma = \frac{(\vec{y}_{k+1} - \vec{y}_k)}{\|\vec{y}_{k+1} - \vec{y}_k\|} - \frac{(\vec{y} - \vec{y}_k)}{\|\vec{y}_{k+1} - \vec{y}_k\|}.
\]

This ensures that the current value of x, used in the Decision layer, increases smoothly as the vehicle travels along the route.

Assuming that the road positions \( \vec{y} \) are accurate and that the vehicle remains on the road, the position error of the localisation method is less than or equal to the position error of the GPS data. Because in the worst case, any position error from the GPS is aligned with the road direction so that the error in x is equal to it. Noting that the VBOX 3i has a horizontal position error of up to 1.2 m (RMS), the time taken to travel this distance at any speed great enough to require deceleration before a curve or road feature will be small compared to the time constants of the vehicle dynamics. We therefore believe that any inaccuracy should have only a minor effect on the functioning of the assistance system. Nonetheless, if more accuracy was desired, measurements of integrated vehicle speed (available from the CANbus/ECU), or of road slope (which is known from mapping data), could be combined with the location x using sensor fusion techniques.

3.2 Long-range radar sensing

The test vehicle is equipped with a front-mounted TRW AC-10 long range radar. This communicates via the CANbus and is capable of simultaneous tracking of up to eight objects in its standard configuration, with a field of view of 12° and an operating range of 2 to 200 m. The radar performs basic signal processing internally to track detected objects, and measurements such as the range, relative velocity and signal strength are output to the CANbus in real-time, along with several flags to indicate whether a tracked object is in the same lane as the current vehicle, and whether it is moving in the same direction, opposite direction or is stationary. The range measurements are accurate to within \( \pm 0.1 \) m and speed measurements accurate to \( \pm 0.1 \) m/s for typical ranges observed during vehicle following.

For implementation of the eco-driving assistance system, these flags were used to perform basic filtering to identify which (if any) of the currently tracked objects correspond to a lead vehicle. This was done by retaining only those tracks in the current lane, and choosing the remaining track with the greatest signal strength. The range and relative velocity of this lead vehicle was then sent to the Decision layer at a rate of 20 Hz.

3.3 Vehicle ECU

Real-time data on vehicle speed, RPM, instantaneous fuel consumption, and many other variables are transmitted from the ECU to the vehicle CANbus at a rate of 100 Hz, where they may be read by the Decision layer. In the on-road prototype described in this paper, the RPM and speed measurements were...
also forwarded to the visual HMI, which doubled as a working speedometer and tachometer. This data from the ECU was acquired and combined by the Perception layer software with the GPS and radar data before being forwarded to the Decision layer at a steady rate of 20 Hz, implying that all filtering and data processing was carried out in less than 50 ms.

4 | DECISION LAYER

4.1 | Fuel consumption model

To determine the acceleration and braking behaviour minimising fuel usage, a mathematical model of instantaneous fuel consumption is required. Rather than explicitly considering gearing, which would complicate the optimisation, we model the instantaneous fuel consumption as a function \( L_f(F, v) \) of the force \( F \) and velocity \( v \) at the wheels of the vehicle. This introduces some error as any particular combination of force and velocity may be achieved in different gears, leading to different operating points for the engine and different resulting fuel consumptions. However, it also greatly simplifies the implementation of the optimisation which does not need to consider the gear ratio. Hence, the mass \( m_f \) of fuel consumed during a journey taking time \( T \) is given by:

\[
m_f = \int_0^T L_f(F, v) \, dt.
\]

(2)

If it is assumed to have a known standard form, such as a polynomial, the function \( L_f(F, v) \) may be found via regression using data from the vehicle under consideration. Note that as this fuel consumption model is static and not dynamic, it necessarily cannot model dynamic effects such as the effect of engine temperature, and hence should be considered valid only in normal operating conditions when the engine has warmed up.

During a test drive, the authors collected data on instantaneous fuel consumption as reported by the ECU and collected from the vehicle CANbus. This test drive was performed on a 21 km route around Southampton, UK, and contained urban, rural and motorway sections driven at an average of 53 km/h. Further info about the route used may be found in the following section on the performed simulator study. This data was split into “training” and “test” subsets in proportions of 80%/20%. Polynomial models of fuel consumption of differing orders were then fit using linear regression. These models had the form

\[
L_f(F, v) = \sum_i \sum_j a_{ij} F^i v^j,
\]

(3)

with the range of \( i \) and \( j \) in each case chosen to retain terms up to the order of the model. The resulting \( R^2 \) values along with the root mean square prediction error (RMSE) estimated by 10-fold cross-validation on the training dataset are given in Table 2. The fourth-order model has the minimum cross validation error, with higher order models showing evidence of overfitting. This model (Figure 2) was selected as the fuel consumption model to be used in the on-road prototyping and the RMSE was also calculated over the test data as 0.2047 mL/s. A comparison of the actual and predicted model values over the test data is provided in Figure 3.

4.2 | Driver preference model

As the assistance system is designed to manage variations in speed due to cornering and vehicle-following, it should model driver preferences in these situations and contain tunable parameters for typical accelerations, following distances, and lateral acceleration limits. In terms of the optimisation, this is accomplished by including a combination of penalty functions that should be minimised to achieve natural car-following behaviour, and inequality constraints that limit acceleration and

| TABLE 1 | Polynomial coefficients of selected fuel model |
|----------|-----------------------------------------------|
| \( a_{ij} \) | \( i = 0 \) | \( i = 1 \) | \( i = 2 \) | \( i = 3 \) | \( i = 4 \) |
| \( j = 0 \) | 3.28e-01 | -2.71e-01 | 1.81e-01 | -2.74e-02 | 1.40e-03 |
| \( j = 1 \) | -2.31e-02 | 7.72e-02 | -1.96e-02 | 1.40e-03 | - |
| \( j = 2 \) | 1.91e-03 | 8.50e-04 | 5.84e-04 | - | - |
| \( j = 3 \) | -1.21e-04 | -5.41e-05 | - | - | - |
| \( j = 4 \) | 2.76e-06 | - | - | - | - |

| TABLE 2 | Comparison of polynomial fuel consumption models |
|----------|-----------------------------------------------|
| Degree | \( R^2 \) (train. data) | RMSE (cross-valid.) |
| 1 | 0.716 | 0.4768 |
| 2 | 0.944 | 0.2129 |
| 3 | 0.945 | 0.2124 |
| 4 | 0.950 | 0.2046 |
| 5 | 0.950 | 0.2064 |
| 6 | 0.951 | 0.2276 |

FIGURE 2 | Contour map of fourth-order fuel consumption model
vehicle speed in curves. The former may be expressed as the integral
\[ S_d = \int_{0}^{T} L_{sd}(s, v, a) \, dt, \]  \hspace{1cm} (4)

in which we have
\[ L_{sd}(s, v, a) = a^2 + \frac{4}{v_d} (v - v_f)^2 + \frac{(1 - s/s_d)^2}{(s/s_d)^2 + 1}, \]  \hspace{1cm} (5)

where \( v \) and \( a \) are the vehicle velocity and acceleration, \( s = x_f - x - l \) is the headway distance to a preceding vehicle with position \( x_f \) and length \( l \), and \( s_d = T_{max} v + s_{min} \) is a desired distance to the preceding vehicle which increases linearly with speed. Further details of the development of the cost function (5) may be found in [22]. To limit the driver’s maximum acceleration, we also constrain \( a \) as:
\[ a \leq a_{max}. \]  \hspace{1cm} (6)

Moreover, a speed-dependent limit on lateral acceleration is applied when the vehicle is following a path of curvature \( \kappa \), leading to a constraint on velocity:
\[ v \leq \sqrt{\frac{\Gamma_{max}}{\kappa + \Delta \kappa_{max}}}. \]  \hspace{1cm} (7)

This may be rearranged as
\[ (\kappa + \Delta \kappa_{max})v^2 \leq \Gamma_{max}, \]
so that we may interpret the velocity bound as the driver applying an upper limit to the lateral acceleration \( \kappa v^2 < \Gamma_{max} \) while allowing for a possible error \( \Delta \kappa_{max} \) in their estimation of the curvature of the vehicle’s path.

The six parameters \( a_{max}, v_d, s_{min}, T_{min}, \Gamma_{max} \) and \( \Delta \kappa_{max} \) are summarised in Table 3 along with some typical values. These parameters were designed to be a subset of those in existing models for cornering and car-following. In the present work, these values were chosen based on observed values in real-world driving, but in a practical system they could be adapted to individual drivers using naturalistic data [23].

### 4.3 Predictive optimisation of vehicle speed

The longitudinal motion of the vehicle is modelled by considering it as a mass subject to forces due to the drivetrain, aerodynamic drag, rolling resistance and road slope. The dynamics may then be expressed as
\[ \dot{v} = F - \frac{1}{2} \rho A \dot{v}^2 - mg(\sin \theta + C_{rr} \cos \theta), \]  \hspace{1cm} (8)

where \( C_d \) and \( C_{rr} \) denote coefficients of drag and rolling resistance and we have assumed \( v \geq 0 \) to simplify those terms. For prediction of the preceding (lead) vehicle position, its dynamics are also included in the optimisation problem as
\[ \dot{x}_f = v_f, \]  \hspace{1cm} (9)

in which the leader velocity \( v_f \) is assumed constant over the prediction interval. To state the optimisation problem, we must also introduce initial conditions for these variables as
\[ x(0) = x_{0}, \quad v(0) = v_{0}, \quad x_f(0) = x_{f0}, \]  \hspace{1cm} (10)

where \( x_{0}, v_{0} \) and \( x_{f0} \) are provided by the Perception layer.

Introducing a parameter \( \alpha \) to trade-off fuel usage with the driver’s preferences, and a shortened time horizon \( T_{th} < T \), the full optimisation problem may now be expressed as:
\[ \begin{align*}
\text{minimise} & \int_{0}^{T_{th}} \left[ L_{sd}(s, v, a) + \alpha L_f(F, v) \right] dt, \\
\text{subject to} & \text{ (6), (7), (8), (9), (10).}
\end{align*} \]  \hspace{1cm} (11)

The effect of the parameter \( \alpha \) is to trade-off the driver’s preferences and the minimisation of fuel consumption [21]. Greater reductions in fuel consumption are possible if following distances and velocities are allowed to vary from their nominal values, so as \( \alpha \) is increased, the fuel consumption of the computed
speed profile will decrease. However, large values may lead to behaviour that is unacceptable to a human driver. The reduction of the time interval from $T$ to $T_h$ modifies the later parts of the solution as $t$ approaches $T_h$. This may be mitigated by including a terminal cost designed to penalise deviations from a target average speed as described in [22]. This optimisation is carried out in a receding-horizon manner, using updated values for the initial conditions (10) and providing feedback to updated measurements. In the on-road prototype, the optimisation was implemented in the ACADO toolkit [24], exploiting its capability for non-linear receding-horizon control. Real-time data from the Perception layer was used to set the initial conditions, and the prediction horizon $T_h = 60$ s. This problem was solved in real-time at a rate of 2 Hz, with a mean computation time of 0.23 s. We made no attempt to shorten this computation time, but it is likely it could be reduced further if code generation techniques were employed. The resulting optimised velocity at $t = 10$ s into the prediction horizon was sent to the Action layer for display, to “coach” the driver into following the optimised trajectory.

5 | ACTION LAYER

5.1 | Visual interface

The result of the predictive eco-driving optimisation was displayed to the driver using a simple visual HMI (Figure 4), consisting of a green and orange “eco-band” overlayed on the vehicle speedometer. This design was chosen from competing alternatives in a collaborative workshop in which interface proposals were rated in several categories using the “Design with Intent” methodology [25]. When in use, the green section extends from zero speed up to the recommended speed received from the Decision layer. The orange region extends above this, allowing some margin for error, and has a width chosen to correspond to the typical root-mean-square deviation of speed in normal driving data when cruising at the speed limit. When in use, the interface updates in real-time at a rate of 60 Hz. As data is received from the Decision layer, the recommended speed changes and the interface smoothly interpolates between values in order to coach the driver into following the optimal speed profile. For the simulator and on-road prototypes, this visual interface was developed in C# using Windows Presentation Foundation as a graphical library. The resulting application is executed on a Microsoft Surface Pro tablet, placed behind the steering wheel of the car to replace the speedometer.

6 | SIMULATOR TESTING

6.1 | Test procedure

For initial development of the eco-driving assistance system, and to allow for a controlled trial of the system on different drivers, the authors developed an initial prototype in a fixed-base driving simulator (Figure 5). This consisted of a 2015 Land Rover Discovery Sport with three large projector screens at the front, an additional screen to the rear, and LCD displays in the side mirrors, to simulate the view from a real vehicle. Engine sounds are simulated using the vehicle’s internal speakers. STISIM Drive was used as the simulation software to display the road environment. Drivers carry out the driving task by using the foot pedals and steering wheel within the vehicle cabin, following a simulated 21 km route around Southampton, UK, with urban, rural and motorway (highway) sections. This is the same route as was used for the determination of the fuel consumption model. The simulation software recorded time-series data including vehicle speed and throttle and brake inputs, which was then used to estimate fuel usage for each study participant based on a detailed quasi-static model of the vehicle powertrain implemented in Simulink, which considered an engine map of fuel consumption losses due to the vehicle transmission, aerodynamic drag, and rolling resistance. These drivers completed the route three times under different conditions: normal driving (“Control”), unassisted eco-driving (“Eco”), and eco-driving with the assistance system enabled (“Band”):

- Control condition: Participants were instructed to drive as they “usually would,” with no other specific instructions. The eco-driving assistance system was turned off, and the
tablet PC in the vehicle cabin showed only a speedometer and tachometer.

- “Eco” condition: Participants were told to drive “as fuel-efficiently as possible,” after being instructed in eco-driving behaviours such as gentle acceleration, avoidance of heavy braking, and maintaining a steady speed. The assistance system was turned off.

- “Band” condition: The eco-driving assistance band was turned on. Participants were told that this speed recommendation would help them conserve fuel if followed. They were encouraged to use the interface as long as it did not interfere with other driving tasks.

To lessen the impact of possible order effects, the study was fully-counterbalanced in that the order in which drivers were exposed to each condition was varied such that an equal number of participants carried out each of the 6 possible permutations. A total of 36 participants took part in the study, with an equal number of males and females. They were aged between 18 and 71 years (mean: 28.9 years, standard deviation: 12.82). All participants were either working in or resident in Southampton and licensed to drive in the United Kingdom, so may be expected to be familiar with the location and roads used for the study, although they may have not previously driven the simulated route. Participants completed two practice drives prior to the main study, one with the assistance system enabled. The route included simulated traffic, which was identical on each repetition of the test. Traffic density was based on early afternoon levels with no jams but some stop-and-go behaviour due to traffic signals, with a stable level of traffic flow in the urban situation (density approx. 10–20 vehicles per mile) and free-flowing traffic in the motorway and rural situations (density <10 vehicles per lane per mile).

### 6.2 Results

A boxplot of the distribution of fuel consumption for the different conditions and road types is given in Figure 6, showing that the median consumption was highest in the Control condition and lowest in the Eco condition for each road type. From physical considerations of aerodynamic drag, we expect that lower average speeds over the route will typically lead to lower values of fuel consumption. Figure 7 shows that this is the case. To estimate the effect of the Eco and Band conditions while controlling for the effects of differing average speed, we fit a repeated-measures ANOVA (GLM repeated measures) model to the fuel consumption data, with Condition and Road Type (Urban, Rural, and Motorway) as within-subjects factors and the average speed in each test condition included as covariates. The data met the standard assumptions (independence, normality of residuals, homogeneity of variances) for use of a linear model. Sphericity was checked using Mauchly’s test, with results indicating that the assumption of sphericity was not violated for Condition ($\chi^2(2) = 4.31, p = 0.116$), Road Type ($\chi^2(2) = 3.38, p = 0.188$), or their interaction ($\chi^2(9) = 13.9, p = 0.126$).

Considering a standard significance level of $\alpha = 0.05$, analysis indicated that both road type ($F(2,64) = 4.57, p = 0.011, \eta^2_p = 0.028$) and condition ($F(2,64) = 15.05, p < 0.001, \eta^2_p = 0.088$) had significant effects on fuel consumption, while their interaction ($F(4,128) = 2.06, p = 0.085, \eta^2_p = 0.026$) did not. Considering the question of whether the Band condition had different fuel consumption than the Control condition, post-hoc analysis using Tukey’s test estimated a 0.249 L/100 km improvement in fuel consumption in the Band condition when the effect of average speed is controlled for (95% CI: [0.084,0.415] L/100 km, $p = 0.001$). Noting that the mean fuel consumption in the Control and Band conditions was 6.501 L/100 km and 6.105 L/100 km, respectively, the overall improvement in fuel consumption in the Band case was 6.09%, which is 3.96% greater than expected from the reduction in average speed alone. There was no significant difference between the fuel consumption in the Band and Eco-driving conditions once average speed was controlled for. Although no significant differences were observed from the Band case, drivers reduced fuel consumption further during unassisted eco-driving by travelling more slowly in aggregate on the motorway. Participants’ average speed in the motorway part of the test showed a mean of 26.1 m/s with a standard deviation of 3.11 m/s in the Eco condition, while for the Band condition the mean was 27.6 m/s and standard deviation 1.92 m/s. Hence, use of the assistance system was associated with an increase in motorway average speed but a decrease in its variance. Interestingly, this led to a decreased number of drivers with average speeds exceeding the legal speed limit of 31.3 m/s (15 during “Control,” which had mean 30.2 m/s and s.d. 3.05 m/s, 1 in “Eco” and 0 in “Band”).
Travel time on the motorway was also improved as a result of this greater average speed, with a mean travel time of 255 s for the 7 km motorway section in the Band condition, 6.48% lower than the mean travel time of 272 s in the Eco condition.

7 On-road testing

7.1 Test procedure

To evaluate the practical feasibility of the system, the authors developed a prototype system on the instrumented vehicle shown in Figure 8. The vehicle is a 2004 Fiat Stilo with a 6-speed automatic transmission, and was equipped with the radar and GPS units used for the study as well as a tablet PC to run the Decision and Action layers of the system.

Two routes were used for testing of the prototype. These are shown in Figures 9 and 10, and were designed to test the response of the system in vehicle-following and cornering situations, respectively. During the car-following test, the driver followed another vehicle on the same route, while the cornering test was carried out when the route was mostly free of other traffic. As the fuel-saving potential of the system was assessed separately in the driving simulator, this on-road testing was limited to a technical evaluation of the system, concentrating in particular on the accuracy of a fuel consumption model based only on velocity and wheel force, and any reduction in performance caused by the need to obtain real-world data from sensors rather than from a driving simulation. These routes were driven three times in each case.

7.2 Results

Figure 11 shows the actual vehicle speed and speed recommended by the system during an 80 s section of the cornering test which contained two consecutive curves. The steering angle and number of visible GPS satellites is also shown. It is clear that the system recommends a lower speed starting around 20 s before the curve at 360 s. The driver, who was instructed to follow the speed recommendation for this portion of the test, uses this recommendation to gradually reduce speed approaching the curve. It is also notable that the speed recommendation...
begins to increase approximately 10 s before the end of the curve, which is expected recalling that the recommended value is drawn from the speed at 10 s into the prediction horizon of the solution of (11). Figure 12 shows the response of the system for a short section of the car-following test, together with the estimated range and velocity of the lead vehicle as measured by the radar. From approximately 850 to 900 s, the speed recommendation increases as the lead vehicle gradually increases its speed, before radar tracking is lost intermittently from approximately 905 to 925 s. Radar tracking of the lead vehicle is recovered at 923 s, where it has come to a halt and the speed recommendation also reflects this fact. This was a common occurrence during the test, with the system often recommending slowing down when it detected a stopped or slow vehicle ahead. Tables 4 and 5, respectively, show the availability of measurements from the the GPS and radar during the tests. For the cornering test, up-to-date GPS measurements were available 98.4% of the time (corresponding to when there were at least four satellites visible), but in the following test, the leader was successfully tracked only 67.3% of the time. This was due to a combination of intermittent errors in tracking such as those in Figure 12, typically caused by other metallic objects, and longer instances in which the lead vehicle was outside of the operating angle of the radar.

### TABLE 4  GPS coverage during test

| # Satellites visible | % of time following | cornering |
|----------------------|---------------------|----------|
| ≥ 3                  | 99.6%               | 98.9%    |
| ≥ 4                  | 98.2%               | 98.4%    |
| ≥ 5                  | 95.4%               | 96.1%    |
| ≥ 6                  | 77.3%               | 90.3%    |
| ≥ 7                  | 10.0%               | 76.2%    |
| ≥ 8                  | 0%                  | 55.1%    |
| ≥ 9                  | 0%                  | 28.1%    |
| ≥ 10                 | 0%                  | 0.9%     |

### TABLE 5  Radar tracking during test

| # Tracked objects | % of time following | cornering |
|-------------------|---------------------|----------|
| ≥ 1               | 94.3%               | 92.2%    |
| ≥ 2               | 69.9%               | 67.3%    |
| ≥ 3               | 55.1%               | 35.4%    |
| ≥ 4               | 27.0%               | 16.3%    |
| ≥ 5               | 7.8%                | 7.7%     |
| ≥ 6               | 2.3%                | 3.5%     |
| ≥ 7               | 0.7%                | 1.2%     |
| ≥ 8               | 0.3%                | 0.0%     |

## 8  DISCUSSION

Qualitatively, the system behaved as expected during the on-road tests, though with some shortcomings in terms of the reliability of the available sensor data with availability of accurate radar measurements only 67.3% in a following situation. This was mostly due to the limited field-of-view of the radar, which may lose track of a lead vehicle if it moves out of this range during cornering, for example. This could, perhaps, be overcome by including leader position and velocity estimates from other sensors such as stereo cameras. These sensors would be available on vehicles with adaptive cruise control (ACC) systems or autonomous vehicles, for which this kind of eco-driving assistance system could be integrated into the ACC or autonomous driving software, replacing the Action layer of the present system by actuation that directly controls the speed of the vehicle to improve energy-efficiency. Although an attractive concept, solving the Decision layer optimisation at a rate of 2Hz would be inadequate for smooth control of the vehicle in such applications, so would need to be increased. For driver assistance, there is also scope to replace the visual HMI within the Action layer of the system with other interfaces, such as a haptic accelerator pedal. To aid with electrification efforts, the model of fuel usage used could be replaced with one of electrical energy usage with only minor modifications to the Decision layer software. This would require negative forces \( F \) and negative consumption rates \( L_f \) to be considered when fitting the model, to allow for the possibility of regenerative braking.

The overall efficacy of the eco-driving assistance, relative to normal and unassisted eco-driving, can be evaluated from the results of the simulator testing. This showed no significant difference between the fuel consumption in the Band (assisted) and Eco (unassisted) conditions once the effect of average speed was controlled for. Both cases showed significant improvements in fuel economy over normal driving for a variety of road types. The higher traffic density encountered in the urban section of simulator testing implies that fuel savings in this section were due to differences in car following and start-stop behaviour. In contrast, in the rural section of the drive we expect that fuel savings were due to different behaviour when approaching curves, as the traffic was free-flowing in this section of the simulator test. The assistance system was designed...
to promote fuel saving behaviour in both curves (for rural driving) and car-following (for urban/motorway situations) and managed to achieve this in both simulator and on-road testing. This reinforces the findings of previous studies showing that eco-driving solutions work in both congested start-stop situations [9] and curves [17] while additionally demonstrating that a general-purpose system can give benefits in both cases. Notably, in the unassisted Eco condition, drivers reduced fuel consumption further by travelling more slowly on average on the motorway, with a negative effect on mean travel time, but this behaviour was avoided when drivers were assisted with the band, leading to a greater average speeds overall and lower variances in the speeds of individual drivers. This is likely due to the system’s design, with the desired speed setpoint $v_{d}$ specified as part of the driver preference model. Average speed was also generally reduced in the Band case compared to the Control case, but much of this was a result of better compliance with the legal speed limit.

8.1 Limitations

The chosen minimum time headway parameter of $T_{\text{min}} = 1.2$ is below the 2 s time headway recommended in most driving rulebooks (including the UK “Highway Code”), as it was chosen based on values of inter-vehicle distance observed in real-world driving. This could be raised to 2 s if desired to improve safety, though we did not do so in the present study to ensure that the system did not recommend slowing down to increase vehicle spacings at typically-observed headway distances. We did not attempt to evaluate the driver distraction effects of the developed visual interface, as eye-tracking capability was not present within the driving simulator at the time of the study. Lateral position data was collected in the simulator relative to the vehicle position in the lane, so that the frequency and severity of lane deviations could be considered in future works. We consider this outside of the scope of the present paper, instead leaving it to a potential future publication investigating changes in participants’ driving styles in the different conditions.

9 CONCLUSIONS AND FUTURE WORK

This paper has covered the implementation and testing of an eco-driving assistance system designed to provide a real-time speed recommendation to a driver to assist them in saving fuel. The results of testing were generally positive, in particular:

- The simplified fuel-consumption model used in the system had an root mean square error in testing of 0.205 mL/s, and achieved an $R^2$ of 0.95.
- The optimisation was successfully implemented in an on-road prototype system and solved in less than 250 ms on average, allowing real-time implementation at 2 Hz.

- The improvement in fuel consumption in simulator testing was 6.09%, which is 3.96% greater than expected from reductions in average speed with the system on.
- Controlling for the effect of average speed, improvements in fuel economy of 0.25 L/100 km were observed, similar to those for unassisted eco-driving.
- Motorway travel times were improved by 6.5% when using the assistance system versus unassisted eco-driving, while incidents of speeding decreased as a result of a reduced variance in speed.

In terms of system implementation, future work should concentrate on improving availability of position and speed measurements for the lead vehicle by the incorporation of alternative sensors. The computation time required for processing in the Decision layer could also be improved, for example, through the use of code generation, leading to an increased update rate and smoother movements of the band on the visual interface. This would also open up other possible applications such as direct control of vehicle speed in an eco-driving adaptive cruise control system.

From a research perspective, a detailed study of how the system affects driving style would give insight into the mechanisms involved in fuel-saving and could lead to improvements in the system via encouragement of specific energy-efficient behaviours, such as coasting. The impact of eco-driving and the deployment of eco-driving assistance on traffic density and flow is also an interesting aspect, but is likewise left to future work.

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REFERENCES

1. UNFCCC: EEA greenhouse gas emissions and removals. https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer. Accessed 9 September 2019
2. Vandenbergh, M.P., Barkenbus, J., Gilligan, J.: Individual carbon emissions: The low-hanging fruit. UCLA L. Rev. 55, 1701 (2007)
3. Barkenbus, J.N.: Eco-driving: An overlooked climate change initiative. Energy Policy 38(2), 762–769 (2010)
4. Jamson, A.H., Hibberd, D.L., Merat, N.: Interface design considerations for an in-vehicle eco-driving assistance system. Transp. Res. C, Emerg. Technol. 58, 642–656 (2015)
5. Orfita, O., Saint Pierre, G., Messias, M.: An android based ecodriving assistance system to improve safety and efficiency of internal combustion engine passenger cars. Transp. Res. C, Emerg. Technol. 58, 772–782 (2015)
6. Daun, T.J., et al.: Evaluation of driving behavior and the efficacy of a predictive eco-driving assistance system for heavy commercial vehicles in a driving simulator experiment. In: 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), pp. 2379–2386, IEEE (2013)
7. Delhomme, P., Cristea, M., Paran, F.: Self-reported frequency and perceived difficulty of adopting eco-friendly driving behavior according to gender, age, and environmental concern. Transp. Res. D, Transp. Environ. 20, 55–58 (2013)

8. Pampel, S.M., et al.: Old habits die hard? the fragility of eco-driving mental models and why green driving behaviour is difficult to sustain. Transp. Res. F: Traffic Psych. Behav. 57, 139–150 (2018)

9. Barth, M., Boniboonsomsin, K.: Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transp. Res. D, Transp. Environ. 14(6), 400–410 (2009)

10. Cheng, Q., Nouveliere, L., Orfila, O.: A new eco-driving assistance system for a light vehicle: Energy management and speed optimization. In: 2013 IEEE Intelligent Vehicles Symposium (IV), pp. 1434–1439, IEEE (2013)

11. Madhusudhanan, A.K.: A method to improve an electric vehicle’s range: Efficient cruise control. Eur. J. Control 48, 83–96 (2019)

12. Lin, X., Görges, D., Liu, S.: Eco-driving assistance system for electric vehicles based on speed profile optimization. In: 2014 IEEE Conference on Control Applications (CCA), pp. 629–634, IEEE (2014)

13. Trommer, S., Höltl, A.: Perceived usefulness of eco-driving assistance systems in Europe. IET Intell. Transp. Syst. 6(2), 145–152 (2012)

14. Asadi, B., Vahidi, A.: Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time. IEEE Trans. Control Syst. Technol. 19(3), 707–714 (2010)

15. Sciarretta, A., De Nunzio, G., Ojeda, L.L.: Optimal ecodriving control: Energy-efficient driving of road vehicles as an optimal control problem. IEEE Control Syst. Mag. 35(5), 71–90 (2015)

16. Kamal, M.A.S., et al.: On board eco-driving system for varying road-traffic environments using model predictive control. In: 2010 IEEE International Conference on Control Applications, pp. 1636–1641, IEEE (2010)

17. Ding, F., Jin, H.: On the optimal speed profile for eco-driving on curved roads. IEEE Trans. Intell. Transp. Syst. 19(12), 4000–4010 (2018)

18. Meschtscherjakov, A., et al.: Acceptance of future persuasive in-car interfaces towards a more economic driving behaviour. In: Proceedings of the 1st International Conference on Automotive User Interfaces and Interactive Vehicular Applications, pp. 81–88, ACM (2009)

19. Simonelli, F., et al.: Human-like adaptive cruise control systems through a learning machine approach. In: Applications of Soft Computing, pp. 240–249. Springer, New York (2009)

20. Fleming, J.M., et al.: Adaptive driver modeling in ADAS to improve user acceptance: A study using naturalistic data. Safety Sci. 119, 76–83 (2019)

21. Fleming, J., Yan, X., Lot, R.: Incorporating driver preferences into eco-driving assistance systems using optimal control. IEEE Transactions on Intelligent Transportation Systems (2020)

22. Fleming, J., et al.: Driver modeling and implementation of a fuel-saving ADAS. In: 2018 IEEE Conference on Systems, Man and Cybernetics (2018)

23. Fleming, J.M., et al.: Adaptive driver modelling in ADAS to improve user acceptance: a study using naturalistic data. Safety Sci. 119, 76–83 (2018)

24. Houska, B., Ferreau, H.J., Diehl, M.: Acado toolkit – an open-source framework for automatic control and dynamic optimization. Optimal Control Appl. Methods 32(3), 298–312 (2011)

25. Allison, C., et al.: Inception, ideation and implementation: developing interfaces to improve drivers’ fuel efficiency. Paper presented at the Chartered Institute of Ergonomics and Human Factors (CIHEF), Hilton Birmingham Metropole, UK, 23–25 April 2018

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