An operating point optimizer for the design and calibration of an integrated diesel/continuously variable transmission powertrain

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Abstract: The use of a continuously variable transmission (CVT) with an integrated engine controller allows great freedom of choice of the engine operating point to deliver the power demanded by the driver. This flexibility places even greater emphasis on the requirement to locate an appropriate engine operating point. A technique has been developed that locates the ideal instantaneous engine operating point by minimizing a simple weighted sum of exhaust emissions and fuel consumption predicted by an artificial neural network. This process may be configured automatically to take account of varying operating or environmental conditions, allowing the optimum performance to be returned by the powertrain controller at all times. The structure has been implemented for a turbocharged and intercooled direct injection diesel engine used as the prime mover in an integrated powertrain. Results are presented that demonstrate the use of the optimizer to derive widely varying operating schedules for the engine, each with associated emissions and economy implications. The optimizer code is sufficiently compact to be incorporated into a practical powertrain control strategy. Experimental work presented in a companion paper has confirmed that this ‘systems’ approach to powertrain control allows the emissions and economy performance of the vehicle to be tailored to suit the particular requirements of the installation.

Keywords: continuously variable transmissions, emissions, fuel economy, diesel engines, neural networks, integrated powertrain control, powertrain calibration

1 INTRODUCTION

It is well established that the use of a continuously variable transmission (CVT) gives the freedom to operate an engine at speeds that are not fixed in relation to the vehicle speed. In addition, the use of electronic engine control allows the engine torque output to be set by the control strategy rather than the driver. When used together, these two features allow the driver’s power demand to be implemented in the most advantageous manner. This has been demonstrated [1–3] as a means to optimize fuel economy by running the engine along a line of minimum brake specific fuel consumption (b.s.f.c.), usually called an economy line. However, this does not achieve the best exhaust emissions performance, which must be considered an equal priority in order to meet legislative limits. The extension of the concept of a single operating line to take account of the best balance in regulated exhaust emissions is the subject of this paper. It is part of a task that requires the implementation of such a target strategy in order fully to assess its success. The implementation results of these proposals are presented in a companion paper [4].

The regulated exhaust emissions are carbon monoxide (CO), unburnt hydrocarbons (HCs), oxides of nitrogen (NOₓ) and, in the case of a diesel engine, particulate matter (PM). Owing to the nature of the various pollutants and their different origins the optimum speed and load for a given power will vary for each of the pollutant species under consideration. Fuel consumption will continue to be a priority and is very likely to be controlled by future legislation in Europe [5] and could be considered as an emission of CO₂. Despite this, fuel economy may only be optimized within the constraints of the relevant exhaust emissions limits. A compromise must be found, taking into...

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account the relative importance of each pollutant and balancing this with the goal of low fuel consumption. Several methods for generating such a compromise have been developed [6] which rely on the user (calibration engineer) to set the relative importance of each pollutant. The engineer must retain an input to the process, although the use of an automated routine to incorporate this expert knowledge into a practical controller calibration is extremely useful. It allows the calibration engineer to concentrate on the engineering issues, minimizing the complexity arising from the implementation.

The approach adopted in this work was to extend the economy line concept to include exhaust emissions. The resulting ideal operating line (IOL) allows the powertrain supervisory controller [4] consistently to select the ideal engine operating point for the conditions. The concept of user defined rankings of emissions has been retained for ease of calibration. The optimizer structure has been designed in a generic fashion, although the data presented here are specific to a demonstrator powertrain. The powertrain used an experimental Ford 1.8 L turbocharged and intercooled direct injection (DI) diesel engine. The engine was fitted with Lucas electronically controlled fuel injection equipment for drive-by-wire control of the engine torque output, a prerequisite for a fully integrated powertrain control strategy. The transmission used was a compression belt drive CVT [7] modified to allow electrohydraulic control of the ratio and hence engine speed. A Johnson Matthey oxidation catalyst was used to treat the exhaust gas.

2 DESIGN PHILOSOPHY

The optimizer function was designed to be incorporated into a supervisory control strategy [4]. The optimizer is used to determine the instantaneous ideal engine speed and torque to deliver the power demanded by the driver. This point is termed the ideal operating point (IOP). There are several considerations that should be addressed in the design of such an operating point optimizer. In particular, the design must include the necessary complexity to describe fully the engine operating point while being sufficiently simple to allow its inclusion in a practical control strategy.

Gradual changes in operating conditions, such as changing water temperature or exhaust catalyst temperature, may be referred to as long-term transients. Such events are important to consider in an operating point optimizer as they will have a bearing on the steady state exhaust emissions output of the engine. Other variables in the same category are engine oil temperature and possibly a measure of combustion chamber temperature. These last two variables were not included here, as they required additional instrumentation not available on the demonstrator powertrain. However, the technique is easily expanded to include them.

A second major consideration is the manner in which the optimizer function reacts to disturbances. Clearly, there are some circumstances in which the powertrain must respond rapidly to driver demand. In order to deliver acceptable drivability under these conditions the supervisory controller [4] allows the powertrain to deviate from the IOL, returning only as the transient is passed. Hence it is unnecessary for the optimizer to take account of these short-term transients. Indeed, it is undesirable since a volatile IOL could lead to undesirable performance characteristics. For this reason, variables such as boost pressure are not included in the optimizer structure. In summary, only those variables that are necessary and sufficient to locate the optimum engine operating point in near steady conditions of operation are included in the optimizer structure.

3 OPTIMIZER STRUCTURE

The structure of the IOP generator is shown schematically in Fig. 1. The task is broken down into several subsections. The principal input to the first block (towards the bottom of Fig. 1) is a set of user defined weightings to determine the relative importance of the various pollutants and fuel consumption. This is the means by which the calibration engineer’s expert knowledge is incorporated into the structure. Secondary inputs are the measured engine coolant temperature and catalyst temperature. These two variables may be used in a series of expressions to adjust the user defined weightings to compensate for cold start conditions. A typical adjustment would be an inversely proportional scaling of the HC weighting to catalyst efficiency, as inferred from catalyst temperature. This would give more emphasis to the optimization of HCs while the catalyst was inoperative. When the catalyst is operational, HCs will be attenuated, making the HC concentration in the raw exhaust less critical.

The second functional block is the operating line optimizer. This function incorporates a model of the
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Fig. 2  Search method for locating IOL

The third and final functional block is the operating line interpolation, which is the interface between the IOP generator and the supervisory controller [4]. Upon receiving a power demand from the supervisory controller the optimizer interpolates along the current IOL to return an IOP in terms of engine speed and torque for the demanded power. The IOP coordinates are returned to the supervisory controller which may either move the powertrain to this condition or decide to

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Minimum (0)</th>
<th>Maximum (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HC</td>
<td>g/kW h</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>NO_x</td>
<td>g/kW h</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>PM</td>
<td>g/kW h</td>
<td>0</td>
<td>24</td>
</tr>
<tr>
<td>Smoke</td>
<td>Bosch</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>B.s.f.e.</td>
<td>g/kW h</td>
<td>150</td>
<td>1000</td>
</tr>
</tbody>
</table>
overrule the optimizer to achieve good transient drivability.

4 ENGINE MODEL

The model used to predict the exhaust emissions (upstream of the catalyst) in the operating line optimizer is an empirical model developed using experimental data from a steady state test cell. These data were used to train a neural network of the form shown in Fig. 3. The neural network is a convenient way of building a fast running empirical model with some useful inherent smoothing. The model uses performance and exhaust emissions data obtained from the steady state engine test facility at Bath. The data used were a subset of the data gathered for a transient engine model [8]. As discussed above, the inputs are engine speed, engine torque and engine coolant temperature. The outputs are the emissions of interest, in this case HCs, NOx, PM, smoke and fuel consumption. If the diesel engine is functioning correctly there should be insignificant production of CO compared with a spark-ignition (SI) gasoline engine. As such, CO was not considered in the optimization process. Proposed future legislation [9] may introduce lower limits for CO production from diesel engine vehicles. In this eventuality, the technique is easily extended to include CO. Any other variable (such as engine noise or currently unregulated pollutants) may also be included if data are available to relate it to engine operating conditions.

4.1 Engine model data generation

Initially a data set was generated by the conventional mapping procedure for the nominal operating conditions, considered as ‘on-design’ points. Speed was varied in 500 r/min steps from 1000 to 4500 r/min. Torque was varied in 10 N m steps from 10 N m to the limiting torque curve (LTC) of the engine at each speed point. Sufficient settling time was allowed at each point to ensure steady results. This map was supplemented with data from a number of ‘off-design’ operating points. The aim was to span the range of conditions expected during long-term transients for the relevant independent variables. In practice this entailed running two maps with the water temperature set artificially low, another with water temperature at the nominal setting and one with water temperature set artificially high. A reduced set of steady state points was revisited at each of these conditions to record the new data. Speed points were 1000, 2000, 3000 and 4500 r/min. Torque was varied in four uniform steps from a nominal 10 N m to the LTC at each speed. All other inputs were held as close as possible to their nominal values. Table 2 summarizes the data recording strategy.

4.2 Training and validation

The network was trained to represent the experimental data using a stochastic back propagation algorithm to minimize prediction errors. A simple evaluation of the quality of the trained network is to calculate the r.m.s. of the error in the network prediction compared with experimental data. Ordinarily a new set of experimental data, not used during the training process, would be used for this purpose. The high cost of data generation prevented this in this case and the training data were re-presented for evaluation of the errors. Consequently the figures shown in Table 3 must be treated with caution, although they show that the network represents the engine data presented to it during training with a reasonable degree of accuracy.

<table>
<thead>
<tr>
<th>Data set</th>
<th>Independent variable</th>
<th>Value of independent variable</th>
<th>Number of speed × load points</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None, design point map</td>
<td>All on nominal</td>
<td>8 × 13</td>
<td>Set-point for water temperature 83 °C</td>
</tr>
<tr>
<td>2</td>
<td>None, design point map, reduced number of points</td>
<td>All on nominal</td>
<td>4 × 4</td>
<td>Set-point for water temperature 83 °C</td>
</tr>
<tr>
<td>9</td>
<td>Coolant temperature very low</td>
<td>25–30 °C</td>
<td>4 × 4</td>
<td>As low as possible on this rig</td>
</tr>
<tr>
<td>10</td>
<td>Coolant temperature low</td>
<td>63 °C</td>
<td>4 × 4</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Coolant temperature high</td>
<td>93–100 °C</td>
<td>4 × 4</td>
<td>100 °C not possible at steady state for some low power points</td>
</tr>
</tbody>
</table>
Table 3 Optimizer network training errors (r.m.s. of percent full scale)

<table>
<thead>
<tr>
<th>HCs</th>
<th>NO₂</th>
<th>PM</th>
<th>Smoke</th>
<th>B.s.f.c.</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.80</td>
<td>6.74</td>
<td>4.64</td>
<td>9.87</td>
<td>2.43</td>
</tr>
</tbody>
</table>

In Fig. 4 experimental data points for NO₂ are superimposed on a surface mesh generated by the network. It can be seen that the network has generalized quite successfully to represent the real data. Figure 5 shows how the shape and position of this surface changes with varying coolant temperature.

Figure 6 shows the pattern learnt by the network for b.s.f.c. production at the nominal 85 °C water temperature. Again the pattern appears to be representative of the superimposed experimental data. Figure 7 shows the variation in b.s.f.c. with water temperature. One of the key advantages of the diesel engine is apparent in this illustration. It can be seen that b.s.f.c. is relatively insensitive to water temperature except at very low power outputs. This is due to the nature of the fuel preparation mechanism and the minimal heat losses in a DI engine. The equivalent data for a spark-ignition (SI) engine operating around stoichiometry would show a more marked drop in fuel economy at low temperatures. It can also be seen that the major part of the operating map is relatively flat, showing the more uniform characteristics of the engine when compared with an SI engine. The relative insensitivity to coolant temperature and flat characteristic of the DI diesel are important factors in achieving good all-round economy and emissions performance [10]. This flat characteristic does limit the improvement possible using a CVT. The part load efficiency is already impressive at non-optimum engine speeds and loads, making the benefits of an IOL less dramatic.

The largest r.m.s. error is for the smoke prediction. This reflects both the highly non-linear nature of the smoke map and the marginal resolution of the fixed displacement smoke meter when used with today’s cleaner engines. The simple network used here cannot represent a sufficiently high-order surface to match the experimental data completely. The r.m.s. error of the HC and NO₂ predictions is better but still significant. This is primarily due to noise in the training data. The network will train to a smooth surface with a minimal error while not following the discontinuities introduced by experimental error. This is considered an advantage in this application as a highly convoluted surface will result in a volatile IOL with no realistic improvement in accuracy of the eventual IOL location.

A subjective evaluation of the results is useful as it allows the trends to be visualized readily, checking to ensure general trends are followed. The model only has three inputs, as such the main two inputs (speed and torque) may be varied across their ranges while holding the third (water temperature) fixed. The resulting data may be presented conveniently as a two-dimensional map or three-dimensional surface. The experimental data may be overlayed and the fit assessed subjectively. This was done for each of the outputs.
smoke levels more accurately. This would allow more discontinuous relationships to be described. This has not been done for two main reasons. The first is that network interrogation times would be increased by adding to the structure. This is not desirable in a model intended to be used in an on-board controller. The shape of the surface learnt is representative and this is more important than its absolute error. The second reason is that smoke is not directly measured during the legislative test. Smoke levels will only influence the test...
result by adding to the PM gathered on the filter paper. Since PM is well represented by the network, smoke is not used in the weighting procedure and is hence superfluous for legislative purposes. Its inclusion in the model is to allow the effect of different operating lines to be studied in simulation. Poor smoke levels are displeasing to the driver and other road users and this consideration may be investigated using the network. If
a more detailed investigation were required it would be sensible to train a new, more complex network to represent smoke levels.

5 RESULTS

5.1 Dedicated lines

The optimizer can be used to generate a vast number of subtly different IOLs by varying the pollutant weightings. However, in the first instance it is instructive to investigate the optimum lines for each of the pollutants in isolation. This is easily achieved by setting all the weightings to zero with the exception of the pollutant under investigation.

Figure 9 shows the resulting ideal operating line for fuel consumption at a water temperature of 100 °C. All weightings are set to zero except for b.s.f.c. (which is analogous to CO₂ production). Superimposed is a map of the network prediction for b.s.f.c. at the same water temperature. The IOL generated lies in the region intuitively seen to be the optimum. It can be seen that, for the engine calibration used here, the optimum line follows the LTC for much of the power range. The calibration used was de-rated from a peak torque of 180 N m to the 130 N m shown here. This was to safeguard the transmission used. The shape of the b.s.f.c. map would be identical in the region shown and the b.s.f.c. IOL for the 180 N m engine would be higher than the de-rated LTC. The proximity of the IOL to the LTC will result in sluggish performance as any demand for increased power would necessitate an increase in engine speed, which takes longer to accomplish than an increase in torque.

Figure 10 shows the ideal line generated if HCs alone are considered. Here the ideal line is some way beneath the LTC. When operating at a steady low power condition the controller can react quickly to any driver demand for more power by raising the torque to the IOL, allowing good drivability. This attribute diminishes at higher power demands until the IOL and LTC converge at a demand of around 45 kW. An ideal line for NOₓ is shown in Fig. 11. Here the ideal line is much lower than the LTC. At lower power demands an extra 15–20 kW may be developed very quickly by raising the fuelling to the LTC. The IOL does not meet the LTC until the maximum power point of 50 kW. Since this can only be achieved at one speed/load combination with this engine, all the IOLs will terminate at this point. Similarly the IOP for zero power is defined as the idle condition of 0 N m and 800 r/min in all cases. This line would allow quite sporty performance but would result in high engine speeds in the steady state, which may be undesirable. As may be expected, the IOL for PM (shown in Fig. 12) is nearly identical to that for HCs. Although not required for legislative purposes, an IOL for smoke was generated (Fig. 13). It must be regarded with caution owing to the inaccurate representation of the smoke learnt by this simple network.

![Fig. 9 Optimum line for b.s.f.c.](image-url)
5.2 Weighted lines

In normal operation the weightings for each of these products will ensure a line that is a compromise between these five cases. The structure allows the compromise to be set manually based on drive cycle results, either from simulation or rolling road tests. Figure 14 shows two lines generated with unity weightings for HCs, NO\textsubscript{x}, b.s.f.c. and PM. Since the emission predictions are normalized within the optimizer structure, this represents a truly equal ranking. The solid line was generated with a coolant temperature of 85 °C, and the dashed line with a coolant temperature of 25 °C. The resulting line for 85 °C is similar to the HC and PM lines generated in the previous section and is a compromise between the two extremes of the b.s.f.c. line and the NO\textsubscript{x} line. The inclusion of both HCs and PM in the optimizing algorithm adds extra emphasis to the
area of the operating envelope that is good for both pollutants. This needs to be considered since it may be detrimental to the NO₃ performance of the calibration. The line is progressive, without undesirable discontinuities, and should allow acceptable drivability owing to its position some distance below the LTC. The line for 25 °C is noticeably higher than that for 85 °C in the low power region. Most of this movement is attributable to the significant increase in NOₓ at higher engine temperatures, pulling the line towards higher speed, lower load regions.

The lines discussed above all have the same optimization goals for all engine power levels. In order to achieve the best overall result over a given test cycle it may be desirable to vary the optimizer behaviour as a function of engine power. An example of this approach

![Fig. 12 Optimum line for PM](image1)

![Fig. 13 Optimum line for smoke](image2)
is seen in Fig. 15, which shows a line with a balance between NO\textsubscript{x} and HCs varying as engine power increases. The weighting for NO\textsubscript{x} varies from 0 at 0 kW to 1 at 50 kW. The weighting for HCs varies from 1 at 0 kW to 0 at 50 kW. This allows optimization for NO\textsubscript{x} in the high power area where it is most troublesome and for HCs in the low power region where NO\textsubscript{x} is less problematic.

6 CONCLUSIONS

A simple yet effective technique has been developed to allow an integrated powertrain controller consistently to choose the most advantageous engine operating point with regard to fuel economy and exhaust emissions. Expert knowledge is represented in the structure in the form of a set of weightings defining the relative importance of each pollutant and fuel consumption. By altering this weighting structure the user may examine the inevitable trade-offs between emissions and fuel economy. To demonstrate the approach, the structure was implemented for a direct injection turbocharged diesel engine as part of an integrated CVT powertrain controller. Results from this exercise show that one of the most apparent trade-offs is that between fuel economy and NO\textsubscript{x}. An ideal line for NO\textsubscript{x} will select much higher engine speeds than an IOL for b.s.f.c., an
important consideration when calibrating such an integrated powertrain. A series of alternative IOLs has been generated that demonstrates these effects and suggests some compromise calibrations aimed at minimizing these conflicts.

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