

## **Operating Point Optimiser for Integrated Diesel/CVT Powertrain**

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### **Application of Powertrain and Fuel Technologies to Meet Emissions Standards for the 21<sup>st</sup> Century**

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## **Synopsis**

A technique has been developed to return the optimum emissions and economy from an engine and CVT using integrated electronic control. A supervisory controller is used to place the engine at the optimum operating point for the demanded power. The *Ideal Operating Line* (IOL) is generated automatically using a simple neural network based routine and updated continuously during operation to reflect changing conditions. Results from a simple simulation are presented here which show the effect of the IOL on vehicle performance over the ECE15 + EUDC.

## **1 Introduction**

The drivetrain under consideration consisted of an experimental 1.8TCi DI Diesel engine, an oxidation catalyst and a belt drive CVT. The fuel injection pump and transmission were electronically controlled. The project used experimental and computer simulation studies to develop the necessary control algorithms. Reduced order models were employed to investigate the relative performance of candidate control strategies by simulation. Selected control methods were then to be tested experimentally in the laboratory to determine the emission and fuel economy improvements. The modified system was also installed in a vehicle for the conventional ECE15 + EUDC drive cycle test and an assessment of drivability.

## **2 Operating Point Prediction**

### **2.1 Definition**

One of the fundamental concepts in the Integrated Driveline Control project was that of an Ideal Operating Point (IOP). This is defined as the engine speed and load which delivers the desired power whilst producing the lowest level of undesirable emissions. A locus of IOPs may be drawn across the engine speed/load map and referred to as an Ideal Operating Line (IOL). The undesirable emissions are more wide ranging than the traditional concern relating to CO<sub>2</sub> (directly analogous to fuel consumption). In the Diesel engine they are CO, uHC, NO<sub>x</sub> and PMs. If the Diesel engine is functioning correctly there should be insignificant production of CO compared to a SI petrol fuelled engine. As such CO was not considered in the optimisation process.

### **2.2 Effect of Varying Operating Conditions**

The emissions performance of the engine will change with operating conditions. Gradual changes in operating conditions, such as changing water temperature, may be referred to as *long term transients*. Such events are important to include in the emissions model as they will have a bearing on steady performance. Boost pressure, injection timing, EGR fraction and exhaust manifold pressure vary

comparatively rapidly. Such variables are not useful when designing an IOL generator. Generally the plant will take some time to move to a new operating point. As such the boost pressure and similar variables will track the operating point with sufficient speed to make their inclusion as independent variables in the IOL generator superfluous. Deviations will be inevitable, the variables will, however, return to their nominal values quickly and may be referred to as *short term transients*.

## 2.4 Implications

- User defined weights to prioritise the different pollutants
- Limited engine emissions model including slow transients only
- Variable weights to account for varying catalyst performance and other relevant environmental considerations

The structure of the IOP generator developed is shown schematically in Figure 1. The task may be broken down into several sub-sections.

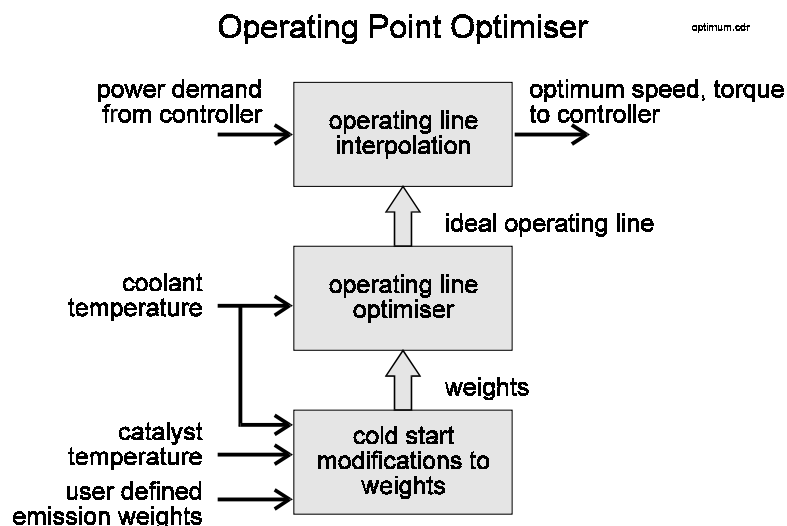


Fig 1 Ideal Operating Point generator - structure

### 3.2 Operating Line Optimiser

The IOL used to set the IOP is determined by a second module, the *operating line optimiser*. This function incorporates a model of the engine which is used to revise the IOL according to changing operating conditions such as coolant temperature.

The line consists of a series of points spaced at 5kW intervals from minimum to maximum engine power. The routine finds the engine speed which gives the lowest predicted weighted sum of emissions for each 5kW power step. Initially a straight 'optimum' line is drawn between the fixed minimum power (at idle speed) and maximum power (at maximum engine speed) points. The engine model is used to predict the emissions at the point where the initial line crosses the 5kW constant power curve. The various emissions are scaled according to pre-determined weightings and summed. This step is repeated at two further points which lie on the same power curve but at lower and higher engine speeds respectively. The point with the lowest weighted sum is chosen as the new 'ideal' point for 5kW. This process is repeated for each power step up to 95% full power. The procedure is repeated at the next controller iteration, which will move the line again in the direction of reduced emissions.

### 3.3 Modifications to Weights

A weighted value is assigned to each of the various emissions considered to describe their relative importance. These weights need not be fixed and can be updated continuously to reflect the prevailing conditions.

The network outputs are normalised over the range 0-1. This process allows the relative weightings of each pollutant to be set more simply. The weights may be modified as a function of coolant temperature and catalyst temperature. The weights may also be varied with power demand. For example, it may be desirable to optimise for HC at low power outputs but as higher power levels are demanded, the emphasis could be switched to minimise NOx production.

## 4 The Engine Model

### 4.1 Structure

The model used to predict the emissions at each step is an empirical model developed using data from a steady state test cell [1]. The data were used to train a neural network of the form shown in Figure 2. The neural network is a convenient way of building a fast running empirical model with some useful smoothing capabilities built into the training process.

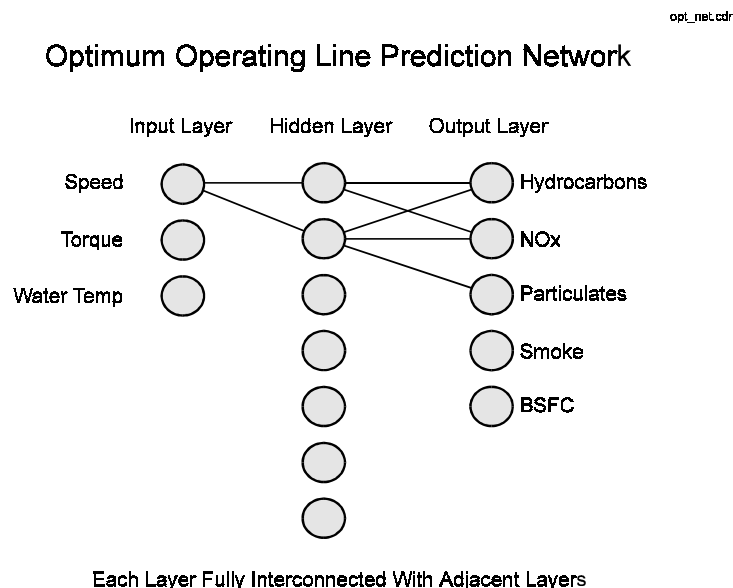


Fig 2 Structure of Neural network

The network was trained using a subset of the data gathered for a transient engine model [2]. In addition to the *on design point* data the maps generated at low and high water temperatures are included.

## 4.2 Training & Validation

The validation task for this model is relatively straightforward compared to the fully transient engine model. 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 superimposed and the fit assessed subjectively. A more objective method of evaluation is to inspect the RMS and standard deviation of the error in the network prediction compared to the training data. The RMS figures are shown in Table 1.

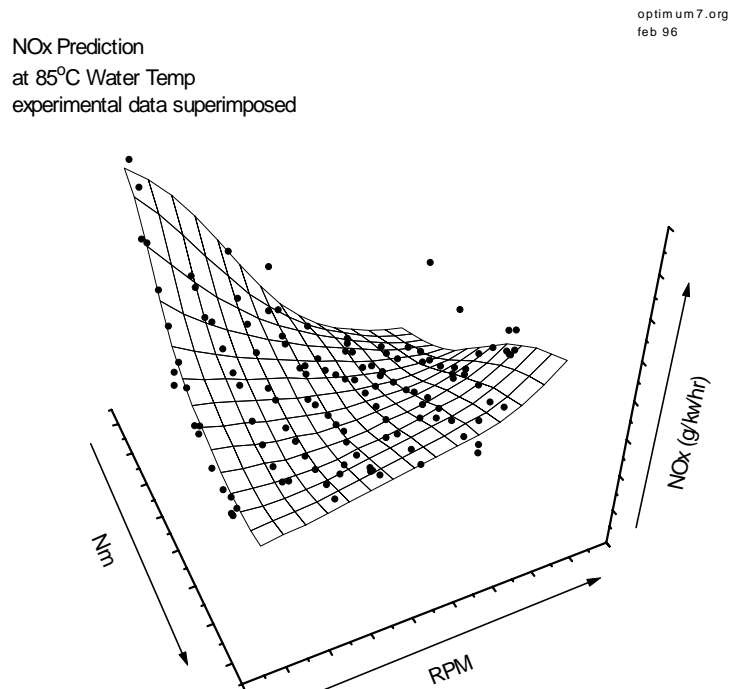
**Table 1** - Optimiser Network Training Errors (RMS as % full scale)

BSuHC	BSNO <sub>x</sub>	BSPM	Bosch	BSFC
7.80	6.74	4.64	9.87	2.43

The figures above show that the network represents the engine data presented to it during training with a reasonable degree of accuracy. The largest RMS error is for the Smoke prediction. This reflects the highly non linear nature of the smoke map. The simple network used here cannot represent a sufficiently high order surface to match the experimental data completely. The RMS error of the HC and NO<sub>x</sub> predictions is better but still significant. However, this is primarily due to noise in the training data. The network will train to a smooth surface with a minimum error. This is useful for the application considered here as a highly convoluted surface would result in a volatile IOL with only minimal improvement in performance.

## 4.3 Subjective Appraisal of Neural Network Emissions Model

An example of the optimiser network output is shown in Figure 3. Experimental data points for BSNO<sub>x</sub> are superimposed on a surface mesh generated by the network. It can be seen that the network has generalised quite successfully to represent the real data.



**Fig 3** Neural Network representation of NO<sub>x</sub> data

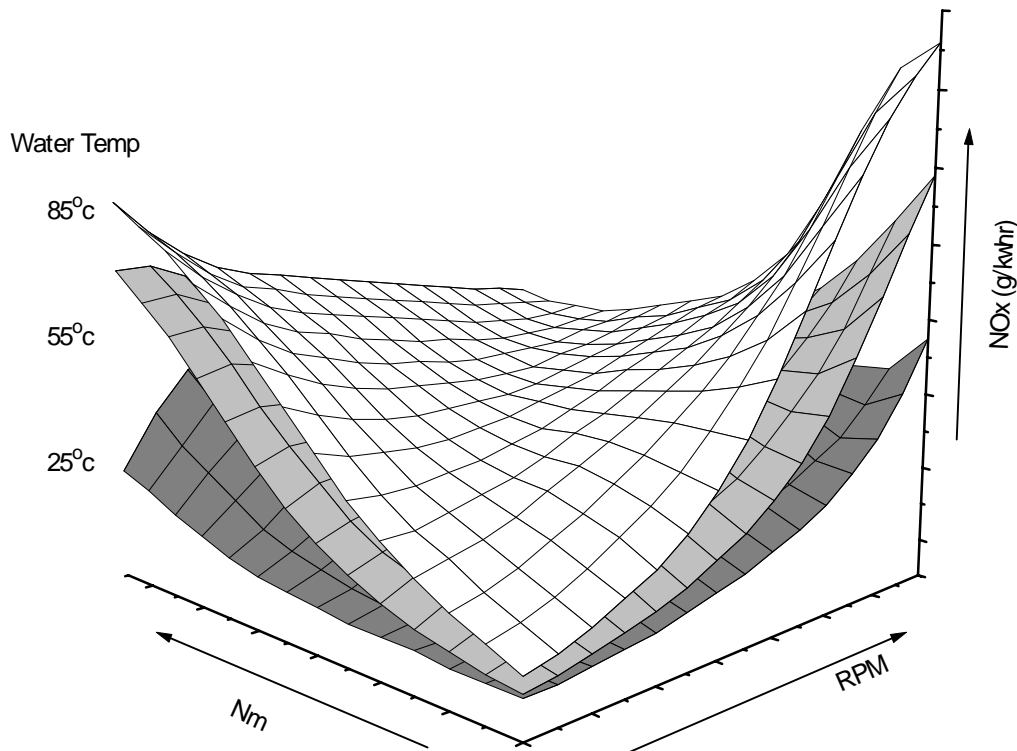


Fig 4 Variation of BSNOx with water temperature

Figure 4 shows how the shape and position of this surface changes with varying coolant temperature. The general characteristic is for less NOx to be produced at lower water temperatures although the shape of the surface does not alter greatly.

## 5 Results

The optimiser can be used to generate a vast number of subtly different IOLs by varying the weightings. In the first instance it was instructive to investigate the optimum lines for each of the pollutants in isolation. This was easily achieved by setting all the weightings to zero with the exception of the pollutant under investigation. In each case the network reproduced the line which would be considered to represent the minimisation of each species. The HC, and BSFC lines are quite similar but the major exception is NOx.

However, in normal operation the user defined weightings for each of the pollutants will ensure a line which is a compromise between these five extremes. Figure 5 shows a line optimised for NOx and HC. The weighting for NOx varies from 0 at 0kW to 1 at 50kW . The weighting for HC varies from 1 at 0kW to 0 at 50kW.

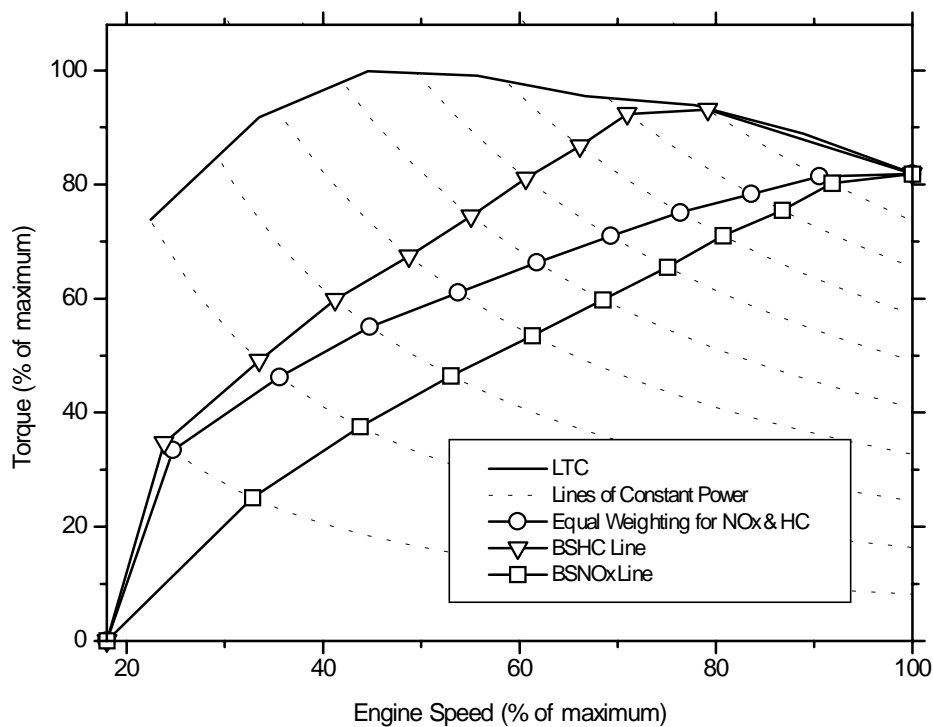


Fig 5 Ideal line with modulated weightings

## 6 Simulated Drive Cycle Performance

### 6.1 Model Structure

In order to investigate the effect of different Ideal operating lines on the emissions performance during drive cycles a simulation was carried out. The simulation is a very simple representation of the system dynamics implemented within an *Excel* spreadsheet. The test is split into one second intervals. For each second the power required to achieve the required vehicle speed is calculated. The engine is constrained to operate on the relevant IOL except in regions of clutch slip when starting from rest or where the ratio range of the unit would be exceeded. The crucial task of emissions prediction at each step is performed by a neural network model of the engine. This model is similar to the network used in the IOL generation except that in this case the mass flow rates of the various emissions are predicted directly in order to simplify the analysis. Results presented here are from a simulation which does not include a catalyst. This simulation tool allows many different strategies to be investigated quickly and easily. Experimental results have indicated that the simulation is sufficiently accurate to allow its use in this fashion. Where more detailed predictions of engine or controller performance are required a fully dynamic simulation may be used [3].

### 6.2 Results

Table 2 presents results from a selection of simulations. Separate simulations were performed with IOLs designed for HC, NOx and fuel consumption. Figure 6 as an example shows the PM mass flows for each run. It can be seen that the HC and BSFC lines are quite similar in their predictions as expected.. This was also true for HC emission and fuel consumption. The major exception is in their production of NOx. The BSFC line produces significantly more NOx. This is due to the engine speeds selected being generally lower for a given power. This is the trade off for the improved fuel consumption, which was the aim of the line. Similarly the NOx line, although producing less NOx as expected, returns significantly worse PM predictions. On balance the HC line appears the best compromise. By inspecting the results from such lines a selection can be made which means that the penalties of each of the more extreme lines are avoided whilst retaining most of their benefits.

**Table 2** - Drive cycle Predictions

Test No.	Ideal Line	HC g/km	NOx g/km	HC+NOx g/km	PM g/km	Fuel L/100km	Excel File
4	HC	0.23	0.50	0.73	0.17	5.86	HC_LINE
8	NOx	0.26	0.46	0.72	0.21	6.16	NOX_LINE
12	BSFC	0.23	0.59	0.82	0.18	5.76	BSFCLINE

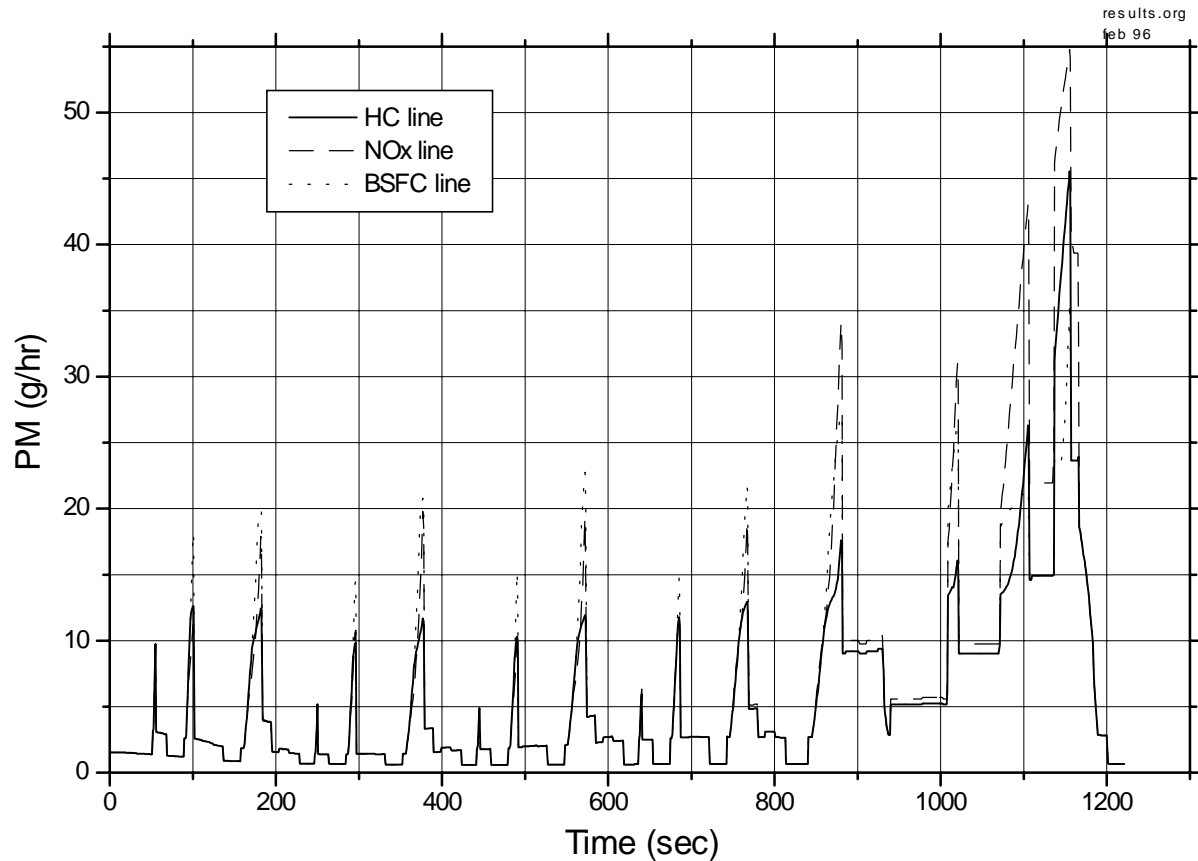


Fig 6 PM predictions

## 7 Conclusion

An optimising routine has been developed which makes use of a neural network based engine emissions model to set an ideal operating line (IOL) for use with an integrated Diesel engine/CVT driveline controller. This allows the supervisory controller to locate the engine at the optimum operating point for the demanded power. The approach used is flexible allowing easy adjustment and tuning of the balance between emissions. The IOL may be updated during operation to reflect the effect of changing conditions on emissions production.

The simple drive cycle simulation technique presented allows a useful preliminary representation of the effects of choice of the IOL. Results are presented which suggest that it is possible to alter the emissions performance of the vehicle significantly over the ECE15 + EUDC test by varying the IOL. The engineer may choose the pollutant to be minimised although a trade off with other emissions is unavoidable.

## References

- [1] Charlton, S.J., Cox, A., Somerville, B.J., Watts, M.J., Horrocks, R.W. - **An Investigation of the Emissions Characteristics of the Passenger Car IDI Diesel Engine.** *IMechE paper C448/025 1992*
- [2] Brace, C.J., Deacon, M., Vaughan, N.D., Charlton, S.J., Burrows, C.R. - **Prediction of Emissions from a Turbocharged Passenger Car Diesel Engine Using a Neural Network.** *IMechE International Conference 'Turbocharging and Turbochargers' 7-9 June 1994.*
- [3] Deacon, M., Brace, C.J., Guebeli, M., Vaughan, N.D., Burrows, C.R., Dorey, R.E. - **A Modular Approach to the Computer Simulation of a Passenger Car Powertrain Incorporating a Diesel Engine and Continuously Variable Transmission.** *IEE Conference 'Control 94*