PERTURBATION/CORRELATION BASED OPTIMAL INTERNAL COMBUSTION ENGINE TUNING

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ABSTRACT—This paper addresses the application of the perturbation/correlation method to optimizing the torque output of internal combustion engines. This application was inspired by observations of the limitations in current techniques of the automotive performance tuning industry. Performance issues such as errors from true optimum spark timing and fuel injector pulse width values as well as convergence were considered for optimal tuning. The ability of the system to deal with engine cycle-to-cycle variations and their effect on input parameters is also analyzed.

KEY WORDS: Internal combustion engine tuning, Optimal tuning, Perturbation/Correlation

1. INTRODUCTION

Current techniques for small scale engine tuning revolve around the concept of a lookup table of fuel and spark advance versus rpm and load as generated by a technician. Typically, this table is generated through trial and error processes utilizing a combination of operator experience and dynamometer data. One major disadvantage of this method is that the operator has no indication of how close they are to the optimum settings. There are no gradient data given to indicate which parameters need to be adjusted or if they should be increased or decreased. Often only the air-fuel ratio is adjusted, as the effect of adjusting several parameters at once is beyond the skill level of the majority of operators. This assumes that torque data from a dynamometer are even available. Often technicians performing the reprogramming are misinformed as to operating conditions that produce favorable torque, such as tuning for minimizing or maximizing the wrong exhaust gasses, such as CO.

The perturbation/correlation technique will be investigated for providing a consistent automatic closed loop direct adaptive technique to engine optimization to replace the current trial and error procedures. This technique would be advantageous as it removes the operator from the loop and uses measured torque data from a dynamometer as the required feedback for updating the parameters. This method would provide enormous flexibility in its application to engines of all kinds without requiring any modification to the software or having user inputs. The values of the optimized parameters could be applied directly to the lookup table, which would allow current engine management computers to be updated without changing their basic structure.

Much work has been performed in trying to optimize engine torque output. Many of these methods involve adaptive controls. The unknown system must be identified if indirect adaptive techniques are to be used. Typically, neural networks or fuzzy logic systems have been incorporated for the system identification role. Once a satisfactory model has been established, standard classical control schemes are used to optimize the system.

Lenz and Schroeder applied a neural network in Lenz and Schroeder (1998) to calculate the amount of fuel required to provide a given air-fuel ratio. Their neural network provided a map from engine speed and manifold air pressure inputs to the fuel mass output. Ignition control using a neural network was tried by Mueller in Mueller and Hemberger (1998). His approach trained a neural network to estimate the optimum spark timing from a data set that was quite extensive. Fuzzy logic has been applied to finding optimal fuel quantities in Jamali et al. (2000). This method uses a self-tuning regulator block and a parameter estimation block in the control diagram. A predictive control strategy was suggested in Sans (1998). The predictive method brings a process to a desired response over a predicted interval. Thus, the engine inputs were adjusted such that the engine output matched the desired output over the range of time specified. This method required the inverse of the engine model response during the predicted horizon.

Ohyama proposed the combination of physical models of an advanced engine control system to obtain sophisticated combustion control in ultra-lean combustion, including homogeneous compression-ignition and activated radical combustion with a light load and in stoichiometric mixture combustion with a full load. Physical models of intake, combustion and engine thermodynamics were incorporated, in which the effects of residual gas from prior cycles on
intake air mass and combustion were taken into consideration in Ohyama (2001).

A parameter identification scheme using input perturbations was used in Ault et al. (1994). This technique used a model developed by Chang that predicts the air-fuel ratio using previous air-fuel ratios, oxygen sensor dynamics, wall wetting coefficient, and several other parameters. These parameter coefficients were identified using dithering of the throttle angle, fuel, and load. Varying these parameters in certain combinations excited the dynamics of the oxygen sensor, from which the required coefficient could be determined. Once the engine dynamics were properly estimated, an LQ controller was used to achieve the desired air to fuel ratio. In Tang et al. (1998), Tang discusses using perturbations of the amount of fuel injected to estimate the air-fuel ratio before the oxygen sensor has warmed up to operating temperature. However, the perturbation analysis is quite different from the perturbation/correlation method. This method was able to fairly accurately estimate the required fuel injection pulse width. This estimate successfully allowed them to use variations in fuel injection pulse width to accurately predict the air-fuel ratio of the next cycle. This value is supplied as feedback to the computer to replace the oxygen sensor output until it has warmed up to operating temperature. It does not provide a means to determine the optimum fuel injection pulse width for torque output or for any other performance index.

2. PERTURBATION/CORRELATION

Perturbation/correlation is a direct adaptive technique in which the unknown system does not need to be characterized. The output is monitored as the input is varied. Based on the behavior of the output, the inputs are adjusted towards their desired final values. Engine output is relatively easily measured using fewer sensors than would be required to train a neural network. The operating points would not wander away from the optimal values as would happen if the neural network did not fully identify a change in the condition of the engine. Currently perturbations are applied to the fuel injection for the equivalence ratio to vary from slightly lean to slightly rich. This approach is used to increase the efficiency of the catalytic converter, and it does not have any relation to the perturbation/correlation method.

The perturbation/correlation method enables the gradient of a function to be found by varying parameters in a sinusoidal fashion. The approach uses an integral correlation method, rather than a numerical derivative, which yields stability and increased insensitivity to noise in the signal. Suppose a function of a parameter is given as $F = \Phi(x)$. A sinusoidal perturbation can be applied to the nominal operating point, $x_o$, that varies with time, $t$, at a frequency of $\omega$.

$$x(t) = x_o + \delta x(t)$$  \hspace{1cm} (1)

$$\delta x(t) = \epsilon \sin(\omega t)$$  \hspace{1cm} (2)

This perturbation yields a set of data points from which the gradient is to be determined. This perturbation is applied over one period of oscillation. The correlation term shall be defined as follows

$$R_i = \int_{t_i}^{t_{i+1}} \delta x(t) \Phi(x(t)) dt$$  \hspace{1cm} (3)

where $2\pi/\omega$, is the time for a single period. This correlation can also be expressed with a summation sampled over time intervals of $t_i = \pi/n\omega$, $i = 1, ..., 2n$ replacing the integral as

$$\hat{R}_i = \sum_{i=1}^{2n} \epsilon \sin\left(\frac{\pi i}{n}\right) \Phi(t_i).$$  \hspace{1cm} (4)

The slope $K$ of the sampling of points $(x(t), \Phi(t); i = 1, ..., 2n)$ is given by

$$K = \frac{\sum_{i=1}^{2n} \left[(x(t_i) - \bar{x})[\Phi(t_i) - \bar{\Phi}]\right]}{\sum_{i=1}^{2n} (x(t_i) - \bar{x})^2},$$  \hspace{1cm} (5)

where $\bar{x} = \frac{1}{2n} \sum_{i=1}^{2n} x(t_i)$ and $\bar{\Phi} = \frac{1}{2n} \sum_{i=1}^{2n} \Phi(t_i)$.

(5) becomes

$$K = \frac{\sum_{i=1}^{2n} \epsilon \sin\left(\frac{\pi i}{n}\right) [\Phi(t_i) - \bar{\Phi}]}{\sum_{i=1}^{2n} \epsilon^2 \sin^2\left(\frac{\pi i}{n}\right)}.$$  \hspace{1cm} (6)

Then, applying the simplifications

$$\sum_{i=1}^{2n} \bar{\Phi} \epsilon \sin\left(\frac{\pi i}{n}\right) = 0$$  \hspace{1cm} (7)

and

$$\sum_{i=1}^{2n} \epsilon^2 \sin^2\left(\frac{\pi i}{n}\right) = n \epsilon^2$$  \hspace{1cm} (8)

yields

$$K = \frac{\sum_{i=1}^{2n} \Phi(t_i) \sin\left(\frac{\pi i}{n}\right)}{n \epsilon}.$$  \hspace{1cm} (9)

Comparing this result with (4) shows that

$$\hat{R}_i = n \epsilon K.$$  \hspace{1cm} (10)

The correlation term is shown to represent the gradient, $K$, of the function at the nominal point $x_o$, multiplied by known constants. Again, this gradient is found using only a simple integral, leading to reliable calculation of the gradient despite noisy signals.

The parameter $x_o$ is updated based on this gradient using the following equation

$$x_{new} = x_o + \gamma \frac{\partial \Phi}{\partial x}.$$  \hspace{1cm} (11)