

Accurate Cycle Predictions and Calibration Optimization Using a Two-Stage Global Dynamic Model

Farraen Mohd Azmin, Phil Mortimer, and Justin Seabrook
Ricardo UK Ltd.

ABSTRACT

With the introduction in Europe of drive cycles such as RDE and WLTC, transient emissions prediction is more challenging than before for passenger car applications. Transient predictions are used in the calibration optimization process to determine the cumulative cycle emissions for the purpose of meeting objectives and constraints. Predicting emissions such as soot accurately is the most difficult area, because soot emissions rise very steeply during certain transients.

The method described in this paper is an evolution of prediction using a steady state global model. A dynamic model can provide the instantaneous prediction of boost and EGR that a static model cannot. Meanwhile, a static model is more accurate for steady state engine emissions. Combining these two model types allows more accurate prediction of emissions against time. A global dynamic model combines a dynamic model of the engine air path with a static DoE (Design of Experiment) emission model. The dynamic model is constructed using a Volterra series model for the EGR response and a Stochastic Process Model (SPM) for boost pressure. Both models are trained using data collected from APRBS (Amplitude Modulated Pseudo Random Binary Sequences) type tests. The static model is an SPM trained using data collected in a steady state DoE test.

The output of the global dynamic model is an accurate prediction of engine emissions with a drive cycle and calibration as model inputs. The global dynamic model is called during the calibration optimization process and the cycle cumulative results are used to control the constraints and optimize the objectives. This produces final calibration maps ready for immediate vehicle tests without test bed validation, thereby improving the efficiency of the calibration process.

CITATION: Mohd Azmin, F., Mortimer, P., and Seabrook, J., "Accurate Cycle Predictions and Calibration Optimization Using a Two-Stage Global Dynamic Model," *SAE Int. J. Commer. Veh.* 10(1):2017, doi:10.4271/2017-01-0583.

INTRODUCTION

Diesel engine calibration requires a powerful optimization process to find optimum engine settings. An optimizer takes into account engine constraints, emission limits and other objectives including map smoothness. The optimization process gets more complex when calibrating an engine with multiple models, for example cold, warm and hot static models to account for engine warm up. Calibration maps are usually optimized against an engine cycle to ensure the engine produces emission levels that meet the regulatory requirements.

One of the limitations in conventional diesel calibration is transient soot prediction. Typically, soot is estimated using a static model trained from a steady state DoE. This method often underestimates soot and may miss some significant soot "spikes" on the transient cycle. An alternative approach is to combine a dynamic air system model with a static soot model. The dynamic model, which can be a physical or empirical model, gives a more accurate air path prediction

transiently, which in turn leads to more accurate transient prediction from the static soot model. [Fig 1](#) shows the different approaches for soot predictions.

Using models for a 4-cylinder light duty diesel engine, this paper discusses the implementation of an empirical air system model and compares it with other global modelling approaches.



Figure 1. Approaches to transient soot prediction

OPTIMIZATION ROUTINE

Calibration optimization is an automated iterative process of adjusting calibration maps to get engine settings that meet optimization objectives and constraints. Fig 2 shows a typical optimization routine for calibrating diesel engine maps. Engine models are important in calibration optimization because they provide engine response prediction values as well as the cumulative emission values. It is obviously important that the predictive values are close to actual values to ensure the optimizer is converging to correct solution. Engine inputs and current calibration settings are fed into the engine model to get cumulative emission values, which are handled as constraints. This ensures the optimum settings meet the required emission levels. A map smoothness constraint is used to limit the gradient and curvature of the final calibration maps. Smooth transition between calibration points is important to prevent sudden changes to engine input variables which are detrimental to drivability and emissions robustness. Meanwhile, map monotonicity constraints may be included to avoid undulations with respect to speed or torque in, for example, the rail pressure map.

The intention of this research is to produce more accurate emission prediction while retaining the established calibration process. To achieve this, a dynamic model is incorporated in the optimization routine to predict instantaneous boost and EGR rate. Fig 3 shows the implementation of a dynamic model in the optimization routine. The objective with this new setup, is more accurate cumulative cycle predictions.

Besides model accuracy, prediction time also is also important when applying a dynamic model because the optimization process can take a significant amount of time to converge to a solution that satisfies all constraints.

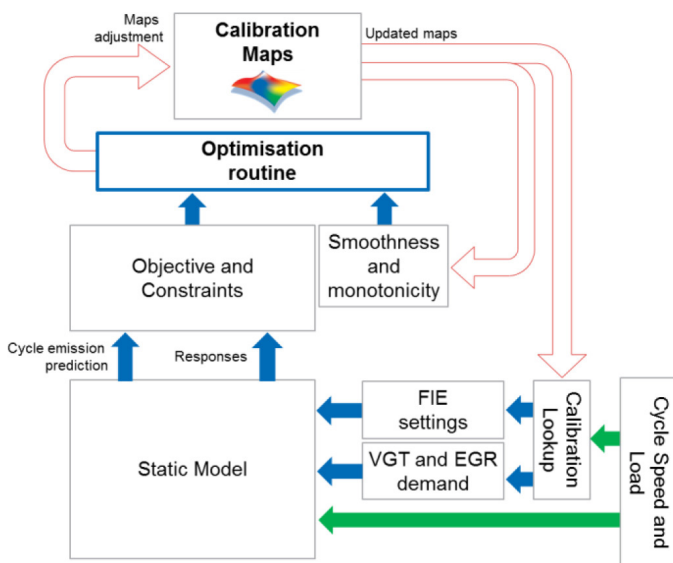


Figure 2. Optimization routine of calibrating diesel engine maps

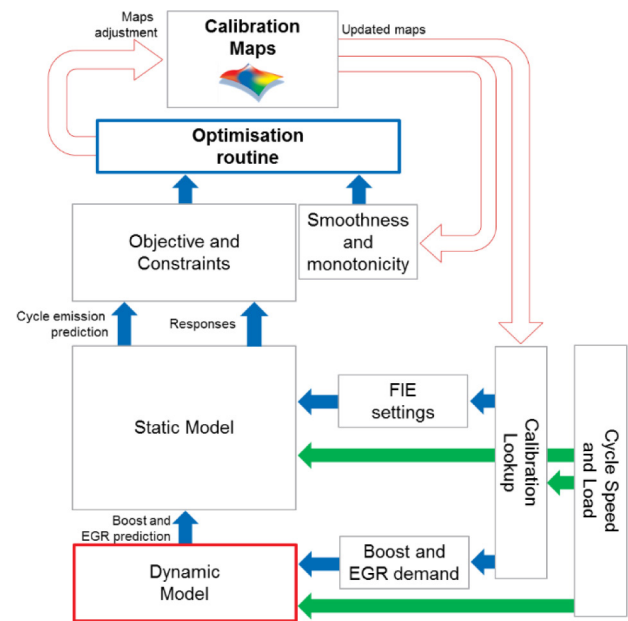


Figure 3. Updated optimization routine with dynamic model

METHODS OF CYCLE PREDICTION

Three methods of transient cycle prediction for diesel engine were introduced in Fig 1:

1. Static model
2. Static model + Physical air system model
3. Static model + Empirical dynamic air system model

In each case, the static model is a Stochastic Process Model (SPM) trained using steady state DoE data. The steady state experimental design had points spread across the entire operating region [1]. At each DoE point, the engine input variables were set and held until the engine condition was stable enough to make a measurement. This data was then used to train the SPM. Fig 4 shows the inputs/outputs of the model. This method predicts time series emissions by feeding the cycle and calibration to a static model (SPM1).

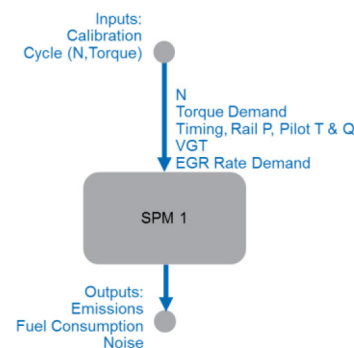


Figure 4. Schematic of SPM1 static model

The second case is not covered in detail in this paper, but results are included later for comparative purposes. The physical air system model is a WAVE-RT [2] model. WAVE-RT is a real-time 1D gas dynamics simulation package. WAVE-RT is coupled with the SPM. In fact, two variants of the static model are employed. The DoE

test, which featured wide variable ranges including boost and EGR levels only observed during transients, was used to create two models: SPM1 & SPM2. SPM1 has the same inputs as in the first case of a static model alone. SPM2 is similar to SPM1, except it uses boost pressure instead of VGT duty as one of its 8 inputs. SPM1 is used to predict the heat release data needed for WAVE-RT and perform certain plausibility checks on the output. The physical WAVE-RT model predicts dynamic boost and EGR rate which are in turn fed into the SPM2 emissions model.

The third approach uses an empirical dynamic model to predict the engine air path. The air path prediction with more accurate dynamics is fed into a static model to get better emission predictions. This method is discussed in more detail in the next section.

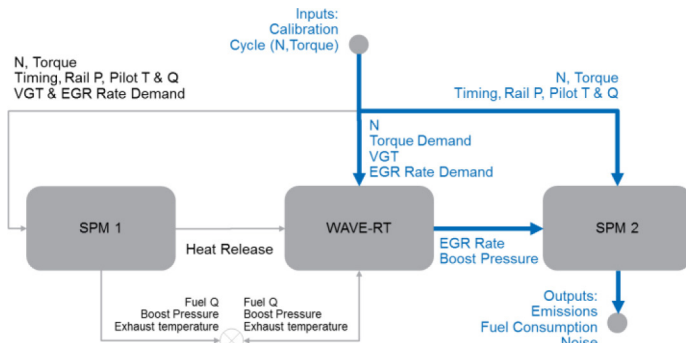


Figure 5. WAVE-RT with SPM2 static model predicting emissions

DYNAMIC MODEL

Dynamic DoE

A dynamic model must be trained with test data. Dynamic models are typically trained with quasi-random data recorded on the test bed or vehicle. Steady state DoE data cannot be used for dynamic modelling because it does not capture the dynamic behavior of a system. Random steps are needed to capture the lagged system outputs. However, DoE methods can be used to design the dynamic experiment.

An APRBS (Amplitude Modulated Pseudo Random Binary Sequence) is a random step sequence that stochastically covers a wide range of amplitudes [3,4]. For engine tests, this imposes severe demands on the dynamometer control system and hardware. Therefore, an alternative sequence based on a sinusoidal rather than square wave was utilized. This might be termed an APRSS with Sinusoidal substituted for Binary in the acronym. Earlier in-house studies have shown the models from sinusoidal data were generally better than pure binary sequences for model quality as well as ease of testing.

Fig 6 shows a section of the APRSS generated for dynamic DoE inputs. The APRSS is constructed using LHS (Latin Hypercube Sampling) and used to train the dynamic model. The APRSS was designed based on the engine operating envelope and covers the WLTC operating region (Fig 7).

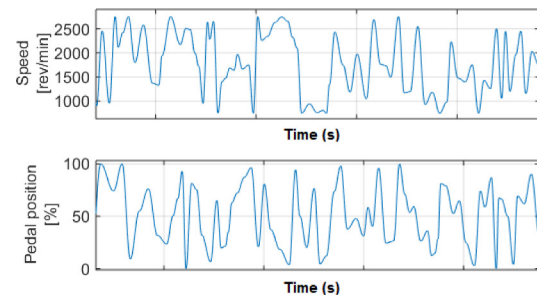


Figure 6. Dynamic DoE Sequence (Sinusoidal APRBS)

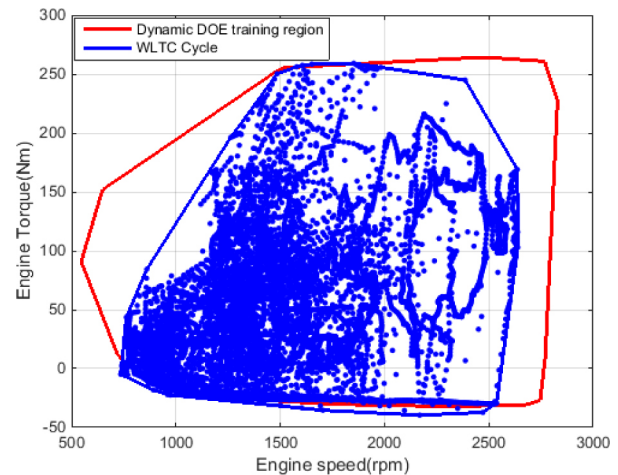


Figure 7. Dynamic DoE sequence region & WLTC points

Model Structure

The model structure contains a function kernel and model constants which must be parameterized. The model structure complexity depends on the system to be modelled. A model kernel can be anything from a polynomial model to a stochastic process model. Model types are selected based on the problem. For this diesel engine calibration experiment, SPM and Parametric Volterra Models gave the best performance.

An SPM was used for boost prediction. SPMs are parameterized using Maximum Likelihood Estimation (MLE). MLE estimates the parameters by finding the parameter values that maximize the likelihood of the sample given the model. The sample in this case is the dynamic DoE test data. The general form of an SPM is:

$$y(x) = \mu + Z(x) \quad (1)$$

Where μ is a weighted mean of the response, y , and $Z(x)$ is a spatial process with mean 0, variance σ^2 and correlation structure, R [5]:

$$R(\mathbf{x}_1, \mathbf{x}_2) = \exp \left(\sum_{j=1}^k -\alpha_j |x_{1j} - x_{2j}|^{v_j} \right) \quad (2)$$

Where $\mathbf{x}_1$ and $\mathbf{x}_2$ are points in the test matrix $\mathbf{X}$, k is the number of variables and α and v are model parameters.