Model-Based Optimal Calibration of a Dual Independent Variable Valve-Timing Engine

Tanya Morton, Richard Connors, Pete Maloney, David Sampson

1. Einleitung/ Abstract

Modern engines have an increasing number of control parameters that are having a dramatic impact on calibration time. Up-front prototyping of calibration processes can be used to reduce the burden of increasing powertrain complexity, however, such techniques are still in their infancy in the automotive field. In this paper we illustrate how flexible model-based calibration tools can be used to prototype a calibration process for an advanced engine type. Specifically, we produce optimal calibration tables for intake and exhaust cam timings that trade off brake specific fuel consumption against NOx emissions. The data used is from a GT-Power model of a production 2.2L naturally aspirated 4-valve overhead-cam spark ignition engine, modified for twin-independent variable valve-timing capability. All analysis techniques used are available in version 2.0 of the Model-Based Calibration Toolbox.

1.1 Introduction

In recent years calibration time has been increasing due to the need to calibrate more advanced types of engines. To reduce this calibration time many companies have turned to a model-based calibration process combined with test bed improvements to allow automation of the data collection process. An additional way of reducing calibration time is to move some calibration tasks to earlier in the design process. Calibration tasks traditionally occur only on the right-hand side of the V design process shown in Figure 1. By performing calibration tasks in parallel with the design tasks on the left-hand side of the V design process, significant time savings can be made.
A calibration process can be prototyped and process-related problems resolved at a stage when they are much less costly to correct. Informed decisions on the design of experiment, model type and optimisation routines expected can be made, allowing for early preparation of initial test plan templates, model templates and optimisation scripts, ready for when the actual engine arrives.

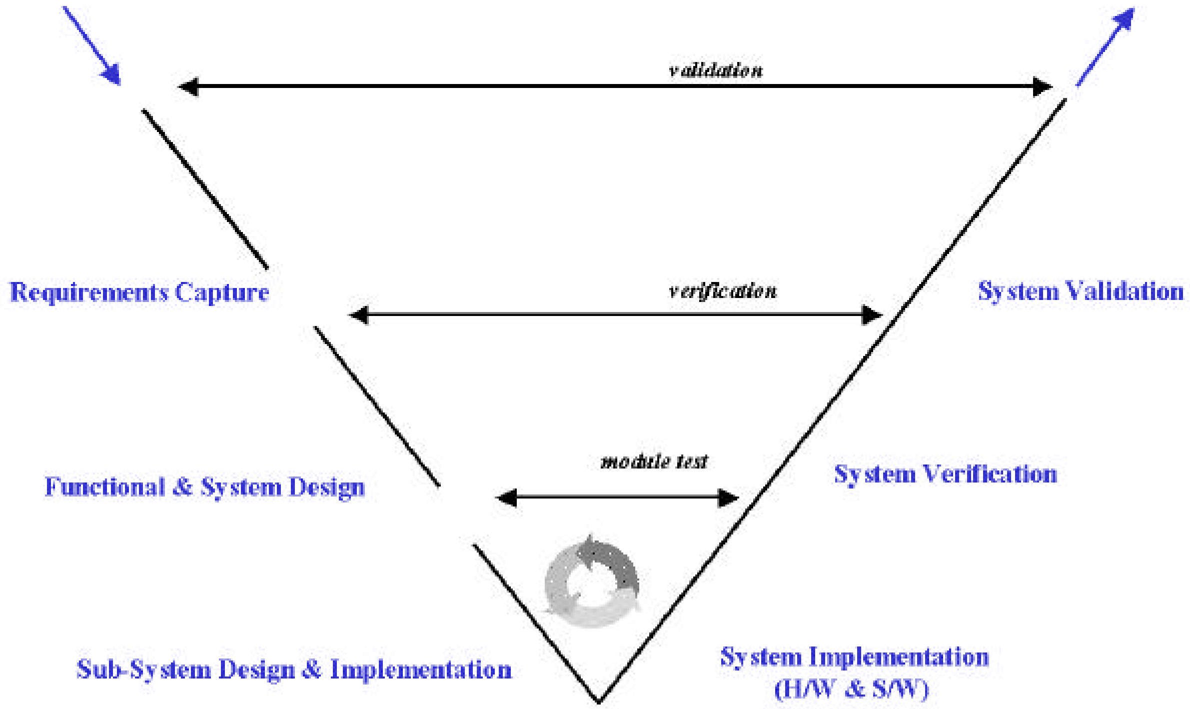

Figure 1: V design process for control development

In this paper we will produce calibration tables for a dual-independent variable valve-timing engine to illustrate a model-based calibration process. The data is collected from a GT-Power model. Physical models, such as those created by GT-Power can be helpful to gain an understanding of engine behaviour early in the design process and to identify data-gathering requirements before test. However, physical models can be time-consuming to run, and this can limit the amount of analysis that can be performed with them. In this paper a statistical emulation of the physical model is produced. The statistical model evaluates much more quickly than the physical model or an engine test, typically in hundreds of microseconds. This opens the door to a greater amount of optimisation and analysis – all of which can be performed before the actual engine is available.

1.2 Problem Statement

The problem addressed in this paper is to produce optimal calibration tables for the three main control parameters: spark advance, intake cam phase, and exhaust cam phase. The inputs to the tables are engine speed and load. Here, load is defined in the typical way as a fraction of the maximum cylinder air charge possible at a given RPM, and based on measured airflow. The values of spark advance and cam positions will be chosen to trade off brake-specific fuel consumption (BSFC) against the amount of engine-out NOx produced, subject to upper limits on catalyst-in exhaust temperature, and intake manifold pressure. The upper bound on intake manifold pressure ensures that there is sufficient vaccum in the intake manifold to allow the use of a brake-servo (booster). The bound on exhaust temperature is to prevent catalyst overheating.

1.3 Design of Experiment and Data Collection

The first step in experimental design is to determine the system inputs (factors) that will be controlled, and the outputs (responses) that should be measured. The inputs are spark advance, intake cam position, exhaust cam position, engine speed, and load. Load was treated as an indirect input, since the test was designed to directly vary scaled throttle position. Output measurements for brake torque, fuel flow, engine-out NOx mass flow, intake manifold pressure, and catalyst-in exhaust temperature are taken.

Of the three control parameters, spark advance has the greatest impact on the responses and the profile of the responses as spark advance changes is distinctive and well-known. We would like to make use of this prior knowledge of the sweep shape to identify outliers in the data and to guide us the modelling process. Moreover, it is relatively quick and easy to change spark advance on the test bed, so a spark sweep can usually be collected efficiently. For these reasons, the data is collected in a series of spark sweeps at different settings of the other variables. The settings of the cam positions, engine speed, and scaled throttle area are chosen using a design of experiment technique.

As this is an advanced engine type, previous experience has suggested that polynomials will not be sufficiently flexible to fully capture the non-linear response and an advanced model type such as radial basis functions (RBFs) may be required [1]. Use of advanced model types precludes the use of optimal design technques, therefore we employ a space-filling design technique with 500 points. As we wish to understand the impact of the cam positions, the full range from –5 (crank-angle degrees advance from base) to 50 degrees (crank-angle degrees retard from base) are tested. This constrains the possible settings for speed and scaled throttle area that can be made.

The data is collected from the GTPower model using a Simulink/Stateflow harness to run the design of experiment points, log data, and monitor misfire and stability.

1.3 Statistical Modelling

The data is modelled using a two-stage modelling approach, see [2] and references therein. Two-stage modelling is appropriate when two distinct groups of variables can be identified: local variables and global variables. The global variables are held approximately constant while the local variables are varied. For example, in our application, the global variables are speed, load, intake cam position and exhaust cam position. These variables are held constant whilst the local variable (spark angle) is swept across its range.

Two stage modelling reflects the underlying structure in the data and can result in more accurate models than if the structure in the data is ignored. Two-stage modelling allows for the possiblity of the error pattern within sweeps being different than the error pattern between sweeps. Prior knowledge of the local sweep shape can be used, and outliers are more readily identified as they can be viewed within the context of the sweep in which they were collected.

The steps to build a two-stage model are:

1. Fit local models to each sweep
2. Identify and remove outliers
3. For each sweep choose a sufficient number of response features to uniquely define the local model shape (e.g. response features could be coefficients if the local model is a polynomial)
4. Model how each of these response features depends on the global variables
5. Combine the response feature models to give an overall description of the system, called a two-stage model.

For example, to build a model for BSFC, in the first step quadratic polynomials are fitted to the data in each local sweep. The spark angle corresponding to minimum BSFC is an important reference point, therefore a datum model of the position is created. This allows the position of minimum spark to be marked on the other response models.

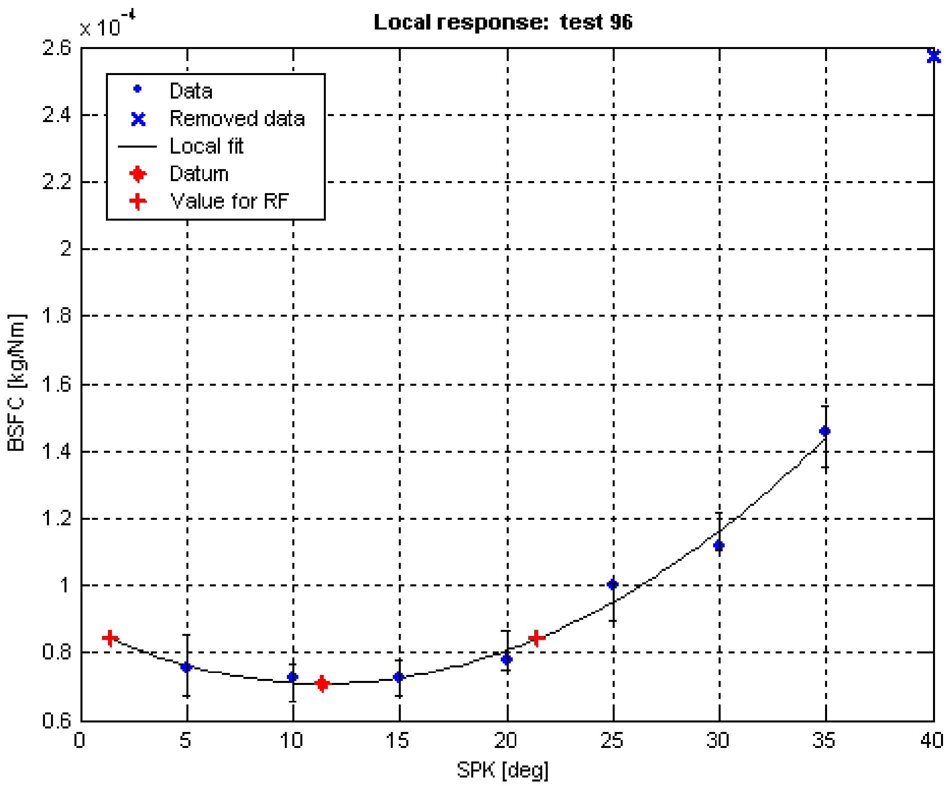

Figure 2: A local BSFC-Spark Sweep

In the second step outliers are identified. This data set contained some sweeps that were very noisy. The GT Power models provide a variable that flags when misfire occurs, and this variable was used to automatically filter out sweeps where misfire occured. These sweeps had higher errors associated with them and removing these points through automatic filtering improved the model quality for this application. All points with very high BSFC or towards the extremes of the spark sweep were automatically removed using the filters 5<= spark <= 45 when engine speed >= 1800, 5<= spark <= 40 when 1300 <= engine speed <= 1800, and 5<= spark <= 35 otherwise.

The range of speed modelled was [1000, 5000]. The range of load modelled was [0.25, 0.95]. Moreover, each local sweep was visually screened and outliers in each of the local sweeps were identified and removed. For example, in the sweep shown in Figure 2, the blue cross indicates a data point that has been selected for removal because its BSFC value is unusually large when compared to the other points in the sweep.
In the third step, response features are measured for each local curve. In this example, the local curve is quadratic and requires three independent numbers (response features) to describe its shape. We chose these response features to be

1. The spark angle that gives minimum BSFC (the datum)
2. The BSFC value at datum plus ten degrees
3. The BSFC value at datum minus ten degrees.

These response features can be modelled well and have engineering significance. They are marked as dots in Figure 2.

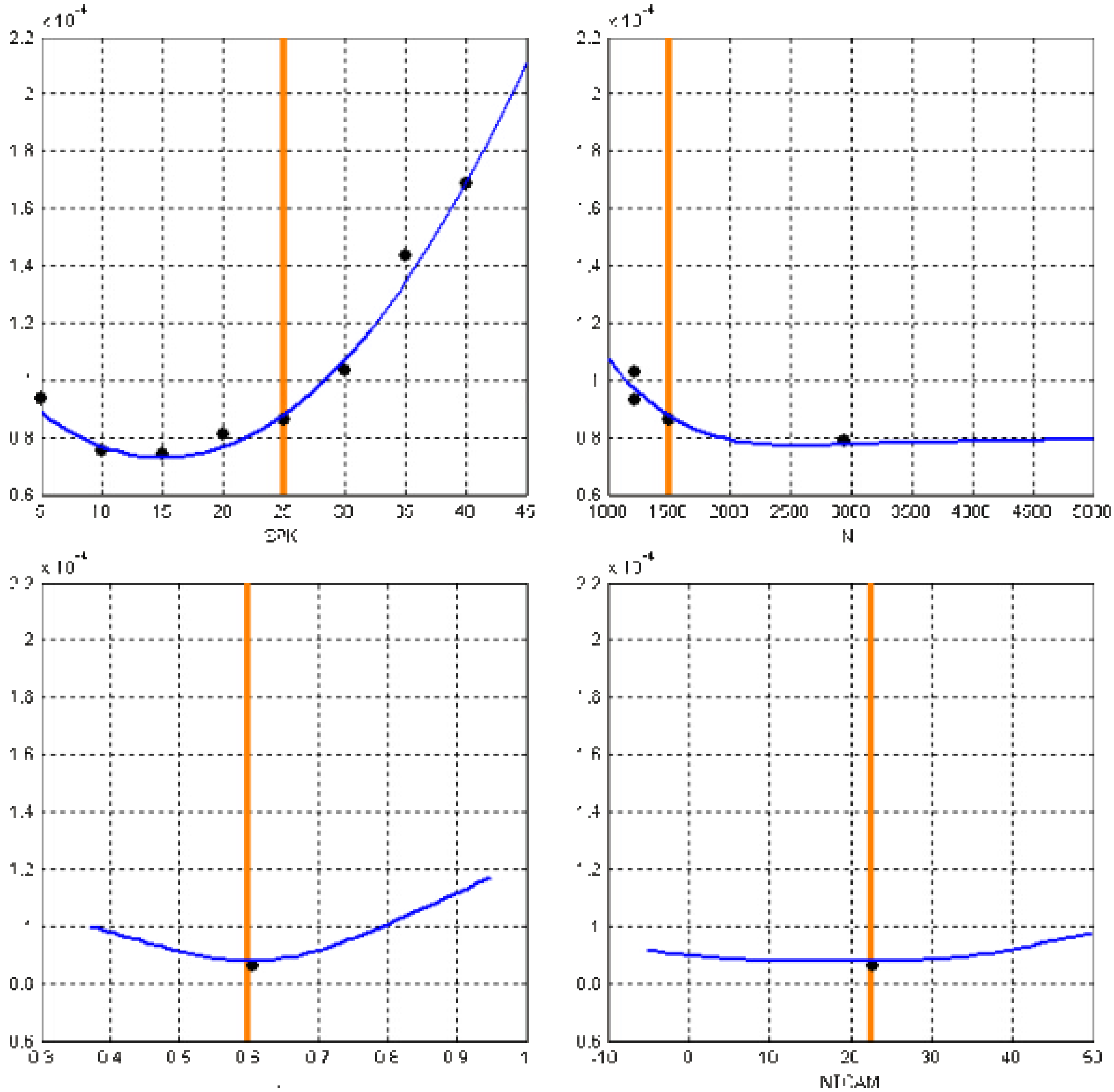

Figure 3: Cross-sectional plots for BSFC at SPK = 25, N = 1500, L = 0.6, INTCAM = 22.5 and EXCAM = 32.7

In the fourth step each of the response features are modelled using a polynomials and a variety of radial basis function models. A radial basis function is a flexible model type that is capable of capturing the complex responses from advanced engine types. For each response feature, the best model is chosen based on the RMSE, cross-validation statistics, qualitative assessment of the model trends, and residual and normal plots. In each case, a radial basis function model (supplemented by a low order polynomial) was superior to the pure polynomial model.

In the fifth step, the response feature models are combined to give an overall (two-stage) model. Maximum likelihood estimation is applied to model the covariance structure and improve the model quality. The maximum likelihood estimation step allows for the possibility of interaction between the response features. Moreover, it takes into account the fact that some sweeps are noisier than others, and therefore should be weighted less in the model fitting process.

The result of the statistical modelling process is models for BSFC, Intake Manifold Pressure, NOx flow, and Exhaust Temperature. Cross-sections of the BSFC model are shown in Figure 3. These models can be exported to Simulink or MATLAB for use in simulations. In this application, we export the models to CAGE, the calibration generation tool in the Model-Based Calibration Toolbox.

1.4 Optimal Calibration

In this study we use the models created to perform constrained optimisations to determine the optimal settings for the control parameters spark, exhaust cam position and intake cam position. The calibration tables are chosen to have 7 values of load and 9 values of speed, equally spaced between 0.35 and 0.95 and 1000 and 5000 respectively. At every speed-load cell we impose the constraints: Manifold Pressure <= 98 kPa and Exhaust Temperature <= 1200K. The amount of NOx that can be tolerated will depend on the value of speed and load, and on how much fuel consumption the calibration engineer is willing to trade off to reduce NOx emissions.

Therefore we pose a multi-objective optimisation problem at each speed-load point in the target calibration table.

$$\begin{aligned}
&\min_{SPK,INT,EXH} BSFC(N_i, L_i, SPK, INT, EXH) \\
&\min_{SPK,INT,EXH} NOx(N_i, L_i, SPK, INT, EXH) \\
&MAP(N_i, L_i, SPK, INT, EXH) \le 98\ kPa \\
&EXTEMP(N_i, L_i, SPK, INT, EXH) \le 1200\ K
\end{aligned} \tag{1}$$

Where:

$MAP - Manifold\ Pressure$

$EXTEMP - Exhaust\ Temperature$

$SPK - Spark\ Angle$

$INT - Intake\ Cam\ Position$

$EXT - Exhaust\ Cam\ Position$

$N_i - Speed\ value\ for\ i^{th} cell\ in\ tables$

$L_i - Load\ value\ for\ i^{th} cell\ in\ tables$

In a more realistic scenario, engine-out hydrocarbon (HC) emissions would also be included as an objective, since HC is known to increase steeply at the high dilution required for low NOx emissions at part-load. Combustion stability constraints would be enforced for vehicle acceptability by including a model of covariance of indicated mean effective pressure (COVIMEP). Knock limits would also be enforced on spark. In this paper HC, COVIMEP, and knock were left out of the analysis because they are not currently available as outputs from the GTPOWER model used in this process demonstration, but in a later phase of testing on a real engine, they could be added to the problem definition. However, assuming NOx requirements dominate the problem, that the NOx model is reasonably predictive, and that staying close to minimum BSFC will avoid HC inflection areas, the problem statement in (1) is reasonable to illustrate a model-based calibration process useful for initial calibration development.

In order to decide an appropriate NOx bound for each table cell, a set of Pareto optimal points is generated at each speed-load point. The Pareto optimal points define the trade off curve. At one end is the point that corresponds to minimum BSFC, and at the other end is the point that corresponds to minimum NOx. The points in between these extremes on the trade off curve represent solutions that are non-dominated, that is, points for which it is not possible to find a setting of the control parameters that give simultaneously smaller NOx and smaller BSFC. This is illustrated in Figure 4. The algorithm used to generate the curve is called the Normal Boundary Intersection Method (NBI) [3].

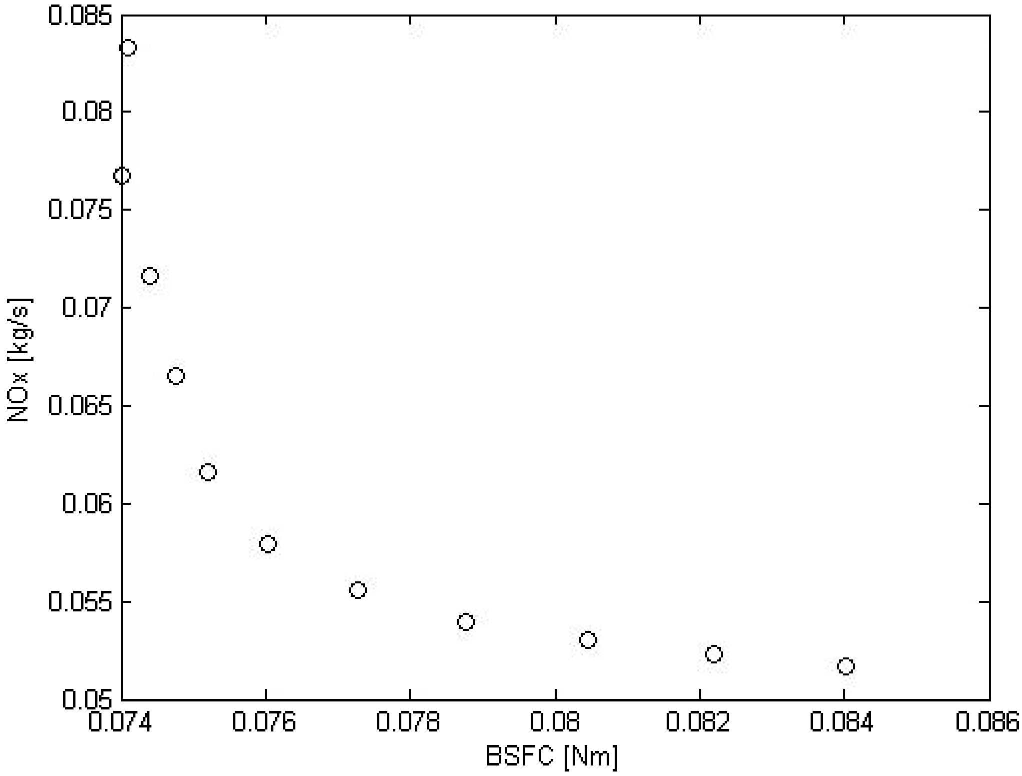

Figure 4: The set of Pareto-optimal points generated for the operating point where speed 4500 rpm = and load = 0.75

For each speed-load operating point of interest, a Pareto solution was chosen that represents a good compromise between small BSFC and small NOx. The guideline used was to select solutions where BSFC was within 5% of its minimum value, provided the corresponding reduction in NOx was significant (above 5%), otherwise the control parameters that gave minimum BSFC were chosen. The solution selected at each operating point depends on the shape of the Pareto curve.

The selected solutions were used to fill the calibration tables. The calibration tables generated are shown in Figure 5. The tables were automatically extrapolated using CAGE to regions where the models do not extend due to lack of data. These tables can be exported for download onto the engine control unit.

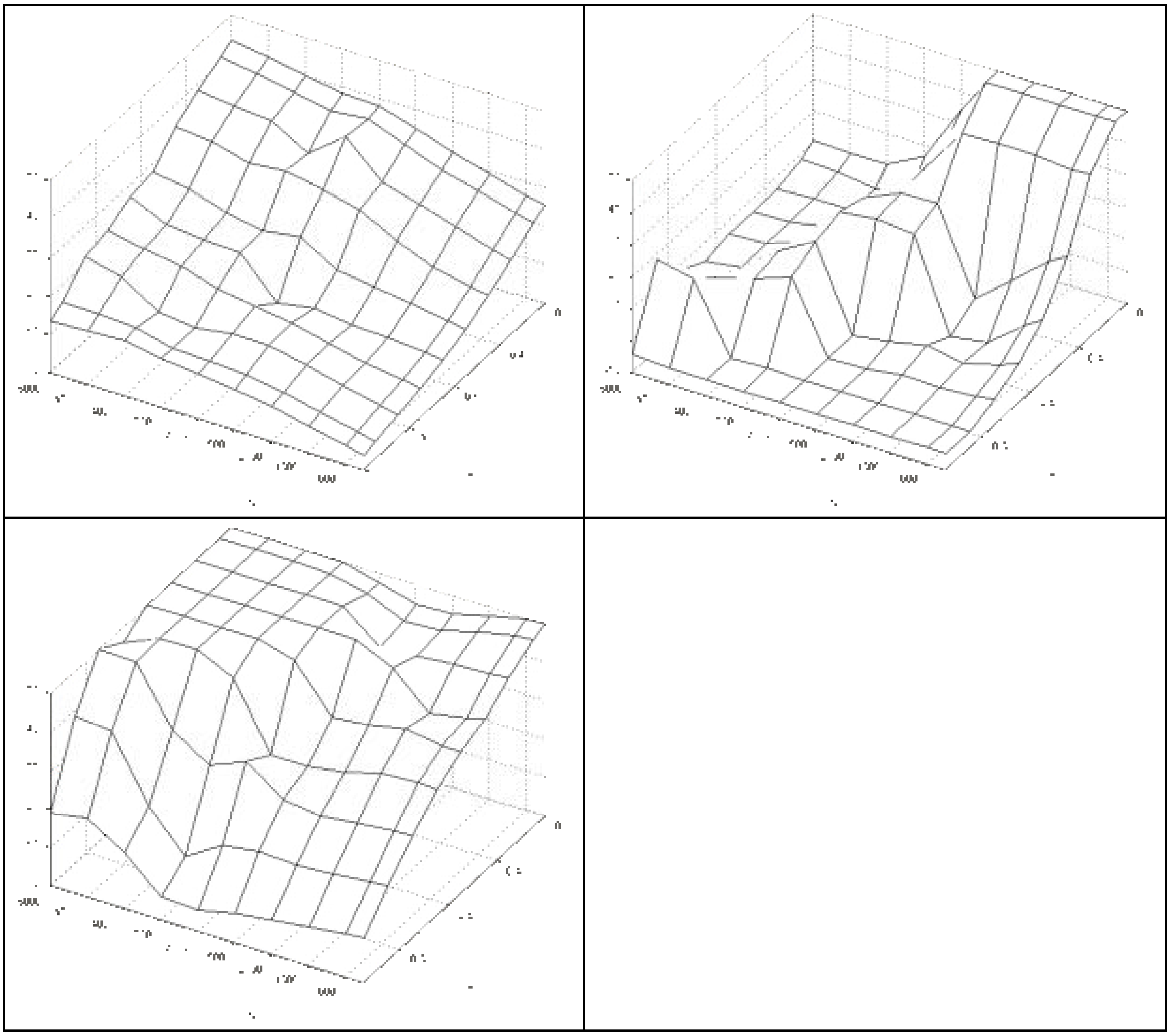

Figure 5: Optimal calibration tables: Spark angle (top left), intake cam timing (top right) and exhaust cam timing (bottom left).

1.5 Conclusions

In this paper we have demonstrated how, using design of experiments and modelling, statistical approximations to physical models can be built and used to generate optimal calibration tables. This approach enables calibration processes to be prototyped early in the design process, which can decrease development time and save costs.

1.6 References

1. Morton T M; Knott S (2002), " Radial Basis Functions For Engine Modelling," , Statistics & Analytical Methods in Automotive Engineering, London, 24-25 September 2002, IMechE Paper C606/022/2002

2. Rose D W; Cary M;Zulczyk S; Sbaschnig R; Ebrahimi K M (2002), "An engine mapping case study – a two-stage regression approach," Statistics & Analytical Methods in Automotive Engineering, London, 24-25 September 2002, IMechE Paper C606/025/2002

3. Das I; Dennis J E, "Normal-Boundary Intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems", SIAM J. Optimization 8 (1998), pp 631-657.

1.7 Contact Information

Dr. Tanya Morton
Dr. Richard Connors
Dr. David Sampson
The MathWorks Limited
Matrix House
Cowley Business Park
Cambridge
CB4 0HH
UNITED KINGDOM

Pete Maloney
The MathWorks Inc.
Crystal Glen Office Centre
39555 Orchard Hill Place, Suite 280
Novi, MI 48375
UNITED STATES