Automated Model Based Engine Calibration Procedure using Co-Simulation

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Abstract: The final validation and sign-off of a production powertrain control module (PCM) calibration is a time-consuming and expensive task and requires a high degree of expertise. There are two main reasons for this; firstly, the validation test is an iterative process due to the fact that calibration changes may affect the true operating point of the engine at the desired test point. Secondly, modifications to the calibration require expert knowledge of the complete control strategy so as to improve the correlation to validation data without potentially negatively impacting the correlated mapping points. This paper describes the implementation of an optimisation routine on a virtual platform in order to both reduce the requirement for experimental testing during the validation procedure, and for development of the optimisation routine itself prior to execution on the engine dynamometer. It is shown that in simulation, the optimisation routine is capable of producing an acceptable calibration within just 5 iterations, reducing the 11-week process down to just a few days. It is also concluded that there are also a number of further improvements that could be made to further improve the efficiency of this process.

Keywords – Engine Calibration Optimisation, Powertrain Co-Simulation, Model Based Calibration; Torque Estimation.

1 - Introduction

Engine calibration validation (the final "sign-off" of an engine Powertrain Control Module (PCM) calibration) is a crucial step in the development of the new engine variant because it is the last chance for engineers to identify and rectify discrepancies between the predicted engine behaviour and actual engine performance as seen by consumers. It is also an incredibly complex task due to the sheer number of parameters and control actuators used on modern vehicles to meet increasingly stringent emissions regulations [1, 2]. At the same time, international legislators are moving away from testing using modal drive cycles such as the New European Driving Cycle (NEDC) and towards highly dynamic test cycles such as the Worldwide harmonised Light vehicles Test Procedure (WLTP) and the Real Driving Emissions (RDE) test in order to bridge the gap between official fuel economy and emissions figures and real-world consumer experience [3]. The combination of these factors is requiring automotive OEMs to not only produce highly efficient engines, but also for them to ensure that they operate efficiently at a wide range of operating points rather than at specific “mapping” points.

This work is part of the Validation Platform for Engine Calibration (VPEC) project funded by the Digital Engineering and Test Centre (DETC) which focusses on the process improvement of the validation of an engine calibration at Ford Motor Company. The validation procedure begins with a completed engine mapping calibration and involves testing the engine on a dynamometer through a series of around 300 steady-state test points using normal operation modes. Once the testing is complete, any error states are identified, and the calibration is adjusted to minimise the error before re-testing. This iterative process currently takes up to 11 weeks from beginning to end and is performed for every unique engine and vehicle variant before going to production.

The aim of this project is to produce a virtual calibration process which can be used to optimise the calibration in conjunction with dynamometer testing, theoretically reducing the number of experimental iterations and significantly reducing the cost and time of the validation process. In addition, as demonstrated in this paper, the validation platform is also being used to test optimisation algorithms developed by The Mathworks which can be used to automate the validation process. Automation of the validation procedure enables 24-hour testing, speeding up the process, as well as reducing the workload on calibration subject matter experts.

2 - Background

Traditionally, engine torque control has been performed by the driver directly controlling a throttle valve. With the advent of turbo-charging, the torque control problem became more difficult, requiring the simultaneous control of both throttle and wastegate to meet the driver demand in the most efficient way [4, 5]. In addition, the torque delivery needs to be smooth, consistent and predictable to the operator.

In modern vehicles, the accurate estimation and control of the brake torque output of an engine is becoming increasingly significant for two main reasons. Firstly, progressively stricter emissions regulations are putting more emphasis on precise engine control, especially for hybrid vehicle architectures; which often require the acceleration demand from the driver to be divided between the engine and one or more electric motors [6, 7, 8]. Secondly, the uptake of Advanced Driver-Assistance Systems (ADAS) and autonomous vehicles are gradually removing the driver from the control loop. Accurate and reliable estimates of the engine torque are required for ADAS, such as for adaptive cruise control [9], shift quality control [10] and engine speed control [11].

In laboratory settings, the engine torque can be effectively measured by the use of a cylinder pressure transducer, however, these sensors are prohibitively expensive for consumer vehicle applications.

Hence it is necessary to estimate the torque indirectly based on the readings from other sensors [12]. Torque estimation is an incredibly complicated task due to the considerable number of design, environmental and control parameters that impact the engine performance. Modern engines have a variety of controllable parameters which will each affect the torque of the engine, ranging from the basics such as throttle position, ignition timing and fuel injection timing to more innovative technologies such as Variable Camshaft Timing (VCT) and Variable Length Intake Manifolds (VLIM). Even small perturbations in any of these can significantly affect the brake torque. In addition, the brake torque will also be affected by environmental conditions in the combustion chamber as a result of variations in intake Manifold Charge Temperature (MCT), Engine Coolant Temperature (ECT) and ambient temperature and pressure. Finally, even though a single engine design may be used in multiple vehicles, its performance will vary between vehicles due to variations in the final implementation, especially with regard to intake and exhaust system installation. Therefore, it is not possible to design and calibrate an engine for one vehicle and then simply use it on another vehicle without re-calibration.

There are a number of different approaches to the torque estimation problem. The most basic of these is a fully “mapped” calibration which uses a series of lookup tables based on engine speed, mass air flow, spark advance, injected fuel mass, etc., which then need to be populated through extensive testing [13]. This is a highly reliable and deterministic method, but suffers from the “curse of dimensionality” as the number of tables increases to include corrections for camshaft timing, Exhaust Gas Recirculation (EGR), etc.. As a result, the time required to populate the lookup tables and the memory required to store them becomes prohibitive for production engines. On the other hand, there are various more advanced indirect measurement techniques such as; sliding mode estimation [14], Kalmann filtering [15, 16, 17], Unknown Input Observers (UIO) [12, 18], adaptive parameter estimation [12, 18] and dirty differentiation estimation [12, 19]. These techniques use the measurement of other engine and vehicle states such as crankshaft speed and manifold pressure to estimate the brake torque in real-time.

The Ford Motor Company uses a semi-empirical model for predictive control of both the air flow and the torque produced by the engine. This technique sits somewhere in between the two categories above, using a number of theoretical assumptions to minimise the requirement for lookup tables. This model is calibrated using empirical data gathered at specific “mapping points” represented by engine speed, manifold pressure and VCT indices. In normal operation, the calibration is then interpolated based on the current state of the engine and the demanded engine torque. This technique balances the requirement for a predictable deterministic response suitable for robust torque control of the engine whilst limiting the requirement for extensive calibration testing. Despite this, the strategy still requires extensive calibration and validation testing to be performed to ensure reliability under real world driving conditions. As a result, it is vital to ensure that testing is performed as efficiently as possible.

3 - Ford Gasoline Engine Control (FGEC) Strategy

A simplified version of the torque control strategy is outline in Figure 1. The strategy works as follows;

1. A torque demand is received by the PCM
2. The torque demand is converted to a normalised cylinder air charge (or "load") demand based on lookup tables.
3. Simultaneously, the engine speed and torque demand are used to determine the optimum variable camshaft timing angles based on a predetermined schedule.
4. The VCT angles, engine speed and air charge requirement are used to calculate a target Manifold Absolute Pressure (MAP) based on a semi-empirical model.
5. The MAP target is used to control the throttle angle and turbo-charger wastegate using a combination of feedforward and feedback control.
6. (The engine responds to the control actuations and produces an amount of brake torque)

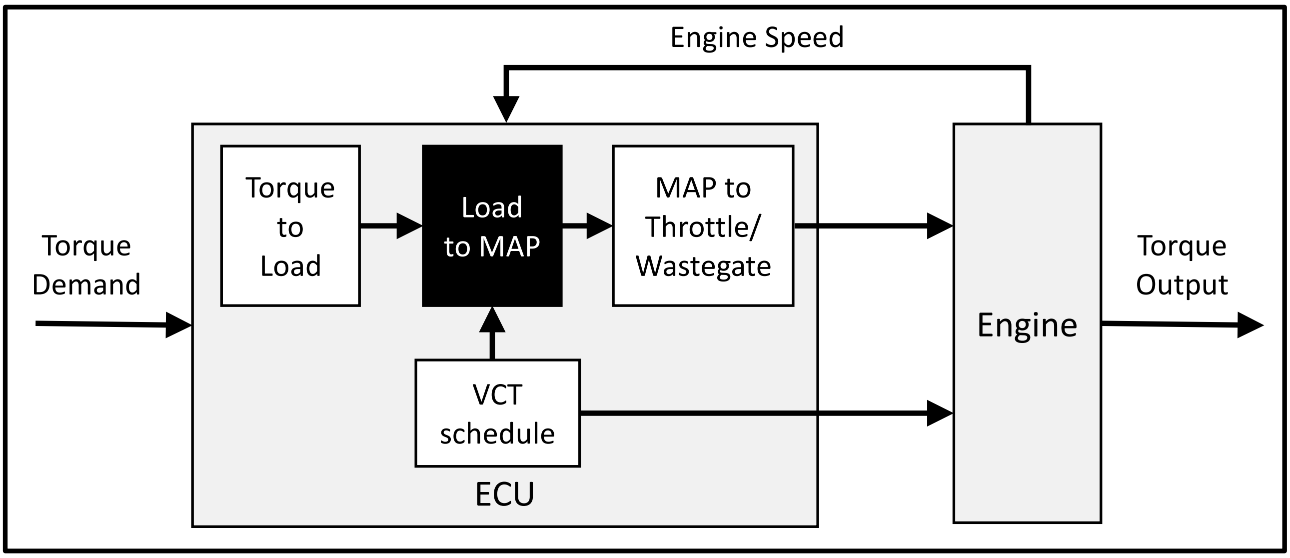

Figure 1 - FGEC Control Strategy Outline

This work focusses validation of the 4th step, the air charge calibration, although the VPEC project as a whole also covers the torque calibration (Step 2). It can be seen from Figure 1 that changes to the calibration will inherently affect the actual operating point of the engine for a given torque demand. This means that any test points affected by a calibration change will require re-testing to confirm the changes have had the desired effect at the new operating point.

4 - Validation Process

The overall process is shown in Figure 2 and described below;

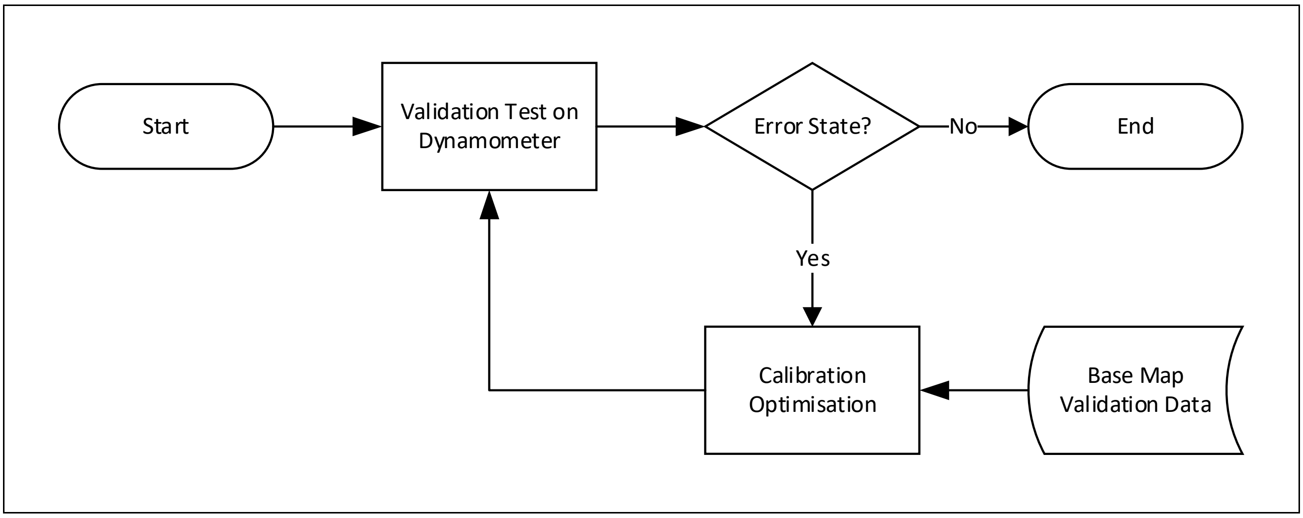

Figure 2 – Validation Process

1. An engine base map and PCM calibration is obtained alongside the base map validation data (around 7500 mapping points).
2. The engine is installed on the dynamometer and the PCM is programmed as closely as possible to how it would be set up in a real vehicle. This means all control actuators are in fully-automatic mode.
3. The test cell is used to run the engine through a set of (around 300) pre-determined speed and torque test points which represent the engine operating range at stabilised engine operating temperatures.
   i. The demand torque and speed are logged alongside the Mass Air Flow (MAF), Manifold Absolute Pressure (MAP), and measured brake torque.
4. The logged data is analysed by experts and the calibration is adjusted to remove error states in the development validation, being sure to also keep the original base map within the error tolerances.
5. The new calibration is re-tested on the engine dynamometer. All test points affected by the calibration change are re-examined.
6. Steps 3-5 are repeated until the error states have been removed.

The validation process is very time consuming because each test point for the validation is dependent on the calibration itself and, due to interpolation, changes to the calibration will also affect neighbouring test points as well as the identified error state. As a result, even relatively minor changes to the calibration can require a large number of test points to be re-examined even if they were previously within the error tolerances.

5 - Co-Simulation Environment

The co-simulation environment consists of three main components; the WaveRT engine model, the PCM or "ECU", and the "Test Scheduler", see Figure 3. The WaveRT engine model is a 0D representation of the 1D air-path engine model created in Ricardo Wave by Ricardo plc. Both the original Wave model and the auto-generated WaveRT model have been correlated by Ricardo plc. with test data provided by Ford. Therefore, for this work, the engine model has been treated as a "black-box" model which simply outputs the engine airflow, manifold pressure and torque based on a number of engine control inputs including; throttle position, wastegate position, camshaft timing, ignition timing, etc..

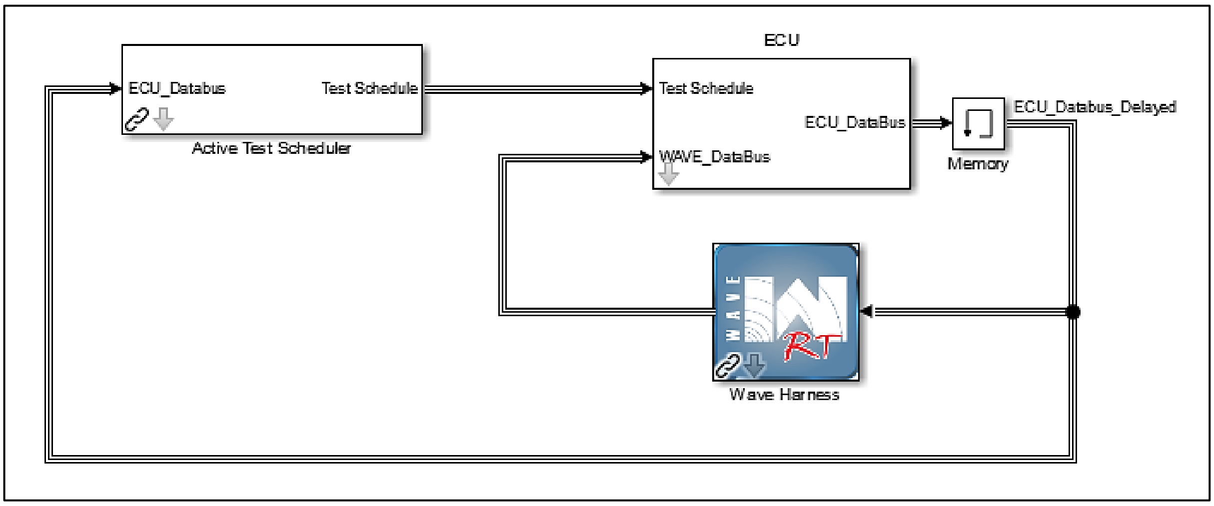

Figure 3 – Co-Simulation Model

The "ECU" block is a Simulink representation of the Ford Powertrain Control Module (PCM) which is parameterised with the calibration to be tested. It takes inputs from the test scheduler in the form of an engine torque demand and uses these in conjunction with feedback from engine "sensors" to manage the engine control inputs.

Finally, the "Test Scheduler" is a state-flow model of the engine test procedure as would be performed by test cell technicians, see Figure 4. The test scheduler is provided with a complete list of the required test points in a given order. It ramps to each test point from the previous one, waits for stabilisation of the operating point, and then takes a measurement as the average value over a set period of time or number of engine cycles. It works through each test point until all required test data have been collected and then shuts down the engine model.

More detailed information about the co-simulation environment is available in a separate paper by Nikolaos Kalantzis [20].

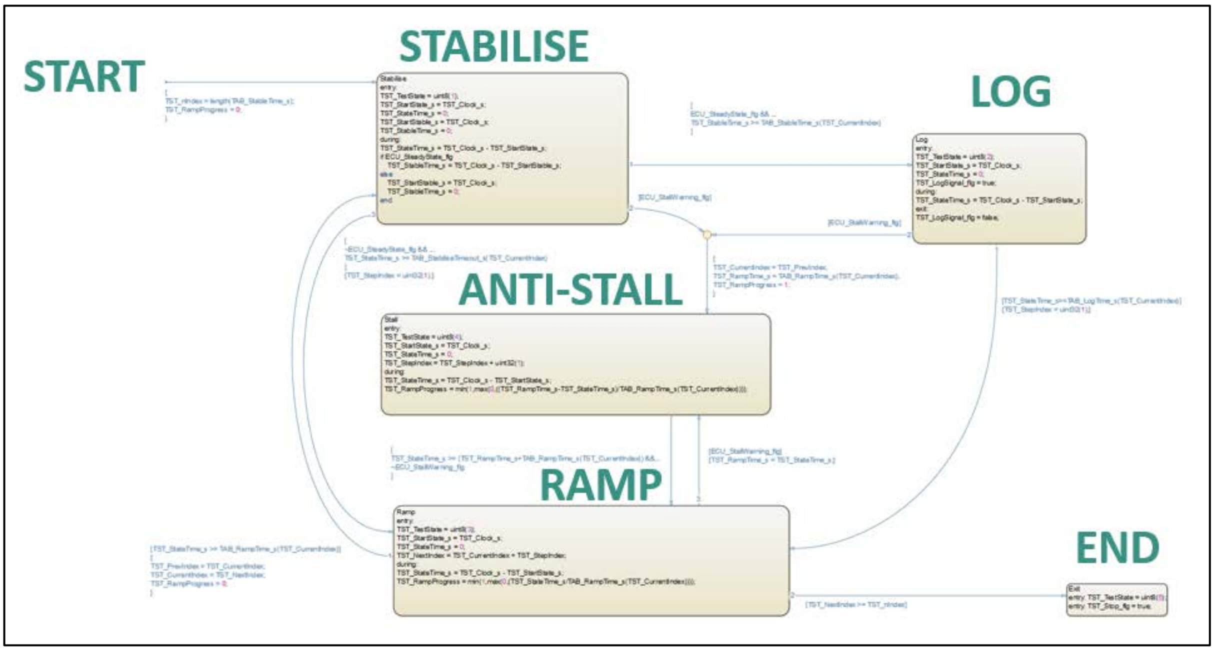

Figure 4 – Test Scheduler Stateflow Diagram

6 - Results & Analysis

The iterative process described in Section 4 was carried out for a 1.0 litre 3-cylinder GTDI engine. The results of the first iteration are shown in Figure 5 and Figure 6. It can be seen in the blue circles in Figure 5 and in the left hand plot of Figure 6 that the original calibration did not entirely meet the measures of Measure of Success (MoS), which is set to ±5% relative error. There were around 10 points which exceeded the desired accuracy, with a maximum residual error of 8.85%. In particular, the calibration tended to overestimate at low speed and medium load, but underestimate at low speed, high load. As both of these areas are critical to real-world usage, this calibration would not be acceptable.

The first run of the optimisation function was able to bring all but one of the error states to within the MoS. However, the optimisation did also push one of the previously acceptable test points outside the desired MoS, meaning that a total of 2 test points were now outside the 5% relative error tolerance, with a reduced maximum error of 6.37%. In addition to the error states, the first optimisation step also reduced the mean residual slightly.

The change in the calibration will have now affected the actual operating point of a number of test points including, but not limited, to those which were error states under the first dynamometer run and therefore another dynamometer test is performed. The results of the second dynamometer test and the second optimisation run are shown in Figure 7 and Figure 8. It can be seen that the maximum relative error was actually smaller than that predicted at the end of the first optimisation run; at just 5.55% for the test point which was pushed outside the MoS in optimisation step 1.

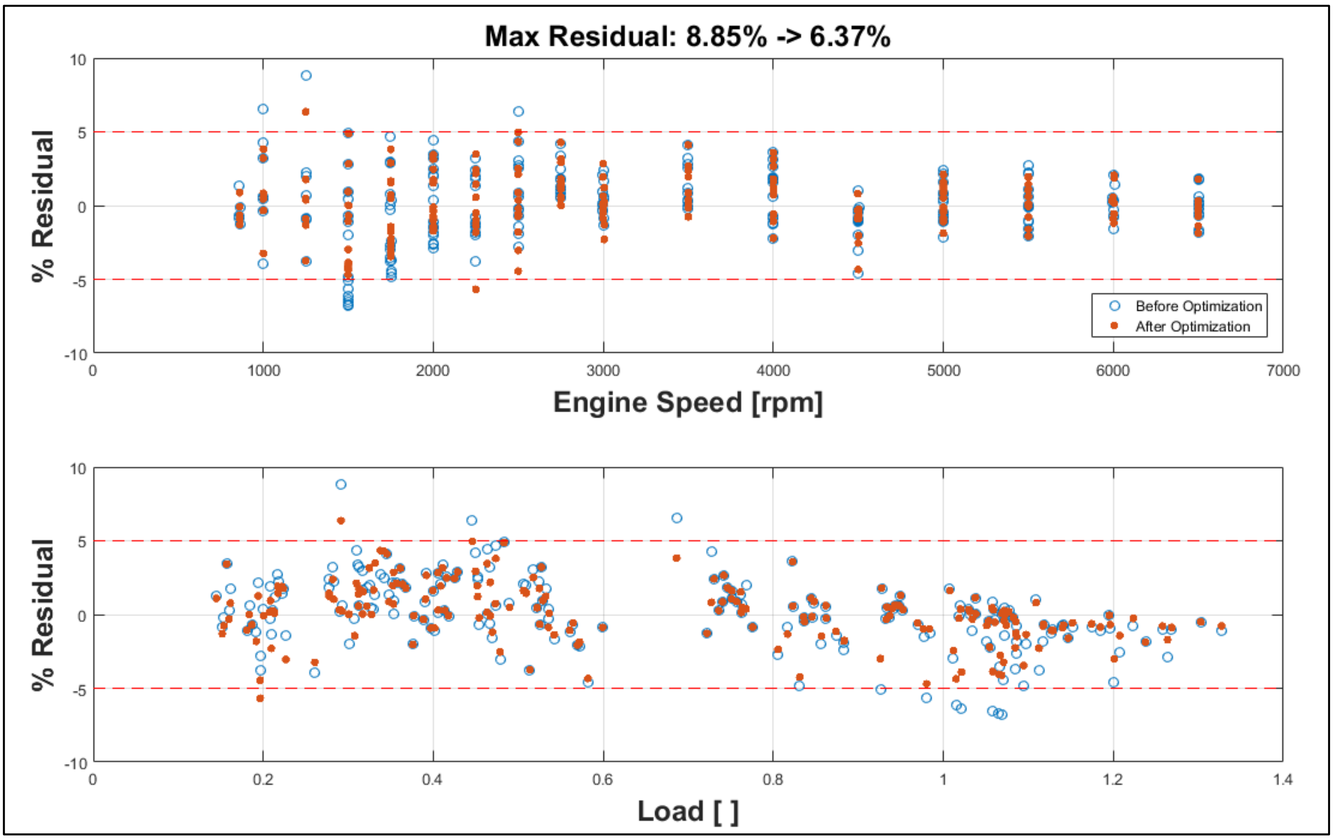

Figure 5 – First Iteration Residuals

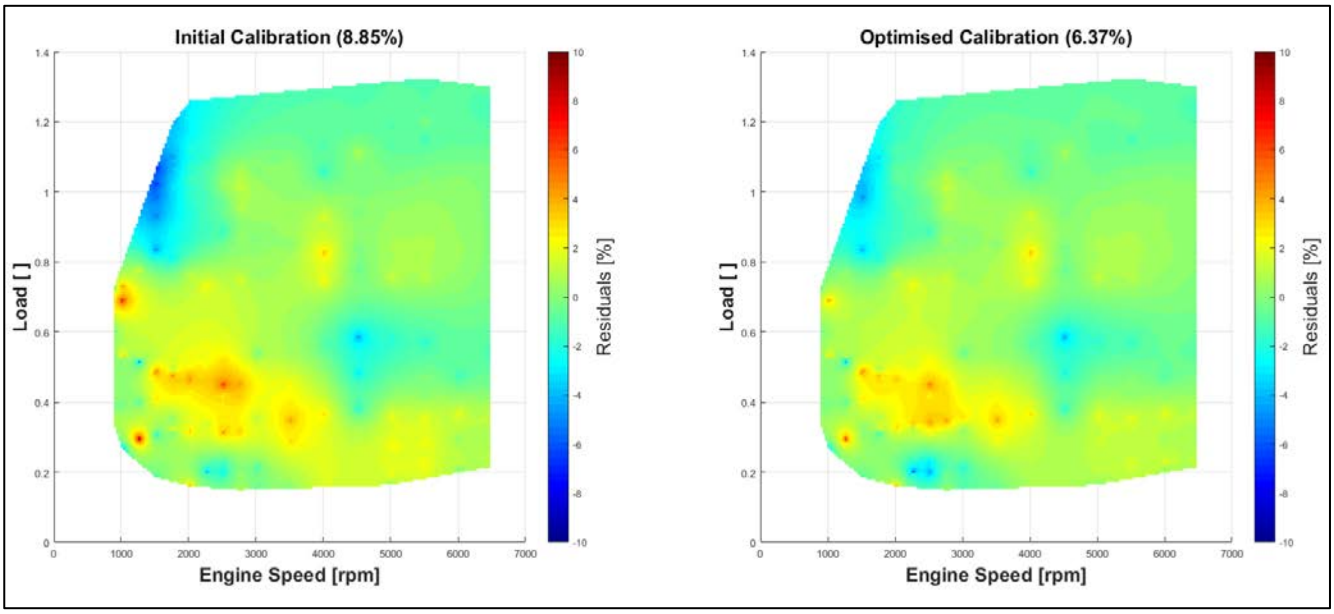

Figure 6 – First Iteration Residual Map

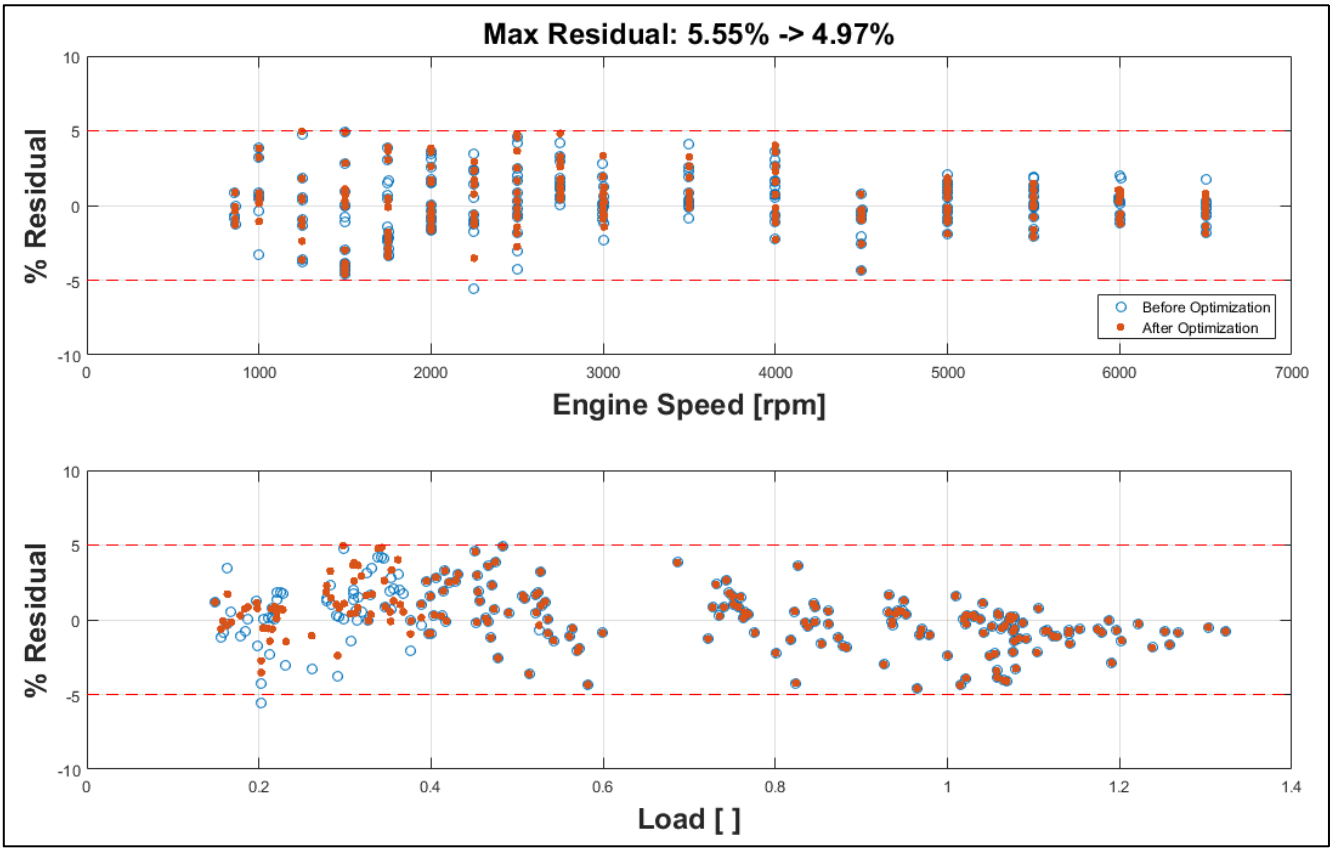

Figure 7 – Second Iteration Residuals

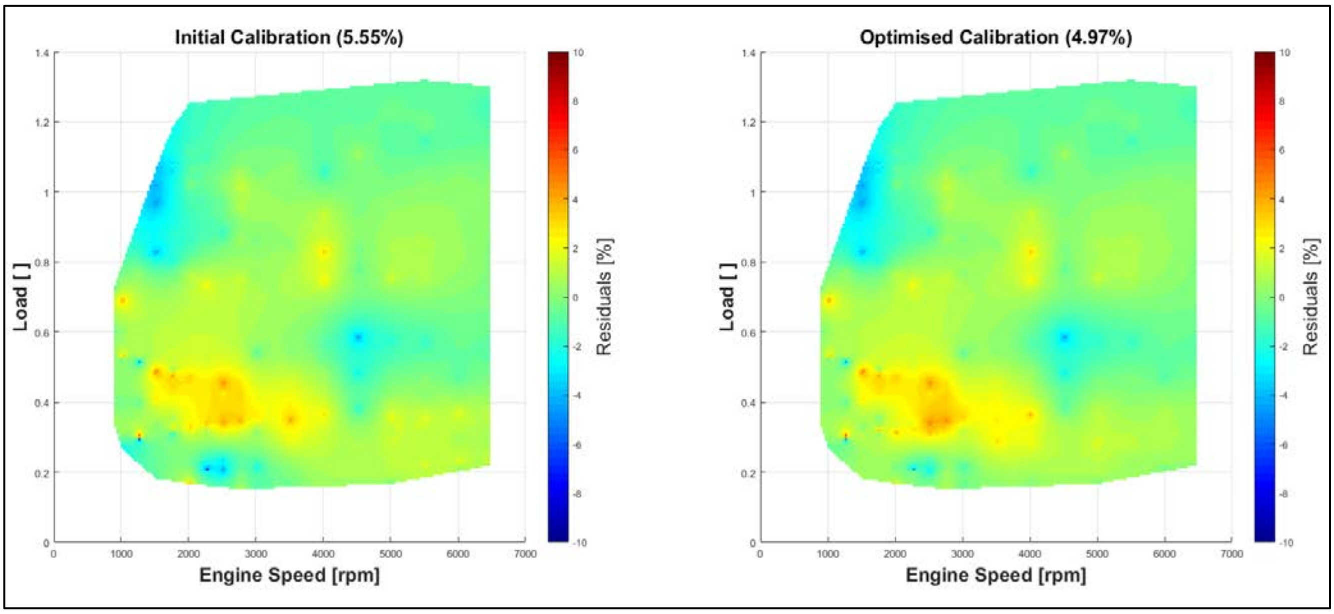

Figure 8 – Second Iteration Residual Map

Examining the results in detail reveals that the previous worst point (+6.37% at 1200rpm) was in fact within the MoS on the second run of the model. This is not necessarily surprising, because the actual operating point of this test point will have changed significantly due to the substantial change in the calibration in this region due to the optimisation routine trying to minimise this error state.

The second iteration was able to bring all test points within the desired MoS with a maximum residual error of 4.97%. However, because this new calibration will have again affected the actual operating point of the engine at each test point, it is still necessary to run the dynamometer co-simulation again. The third co-simulation run showed that the change in calibration had pushed the maximum residual back outside the MoS when accounting for the change in actual engine operating point and therefore the process was iterated twice more until the results of the co-simulation were within the pre-defined MoS. In total, this took a total 5 simulations and 4 optimisation runs, see Figure 9.

Each validation test run took around 1.5 hours running on a 4-core parallel simulation, which was equivalent to around 9 hours of experimental testing. The optimisation routine took around 1 hour to complete for each iteration, resulting in a total simulated optimisation time of just under 12 hours. However, simulation is not the end goal of the project and therefore it is useful to consider the total time for the experiment on a dynamometer which would be around 49 hours, a significant improvement from the 11-week turnaround time for the manual procedure.

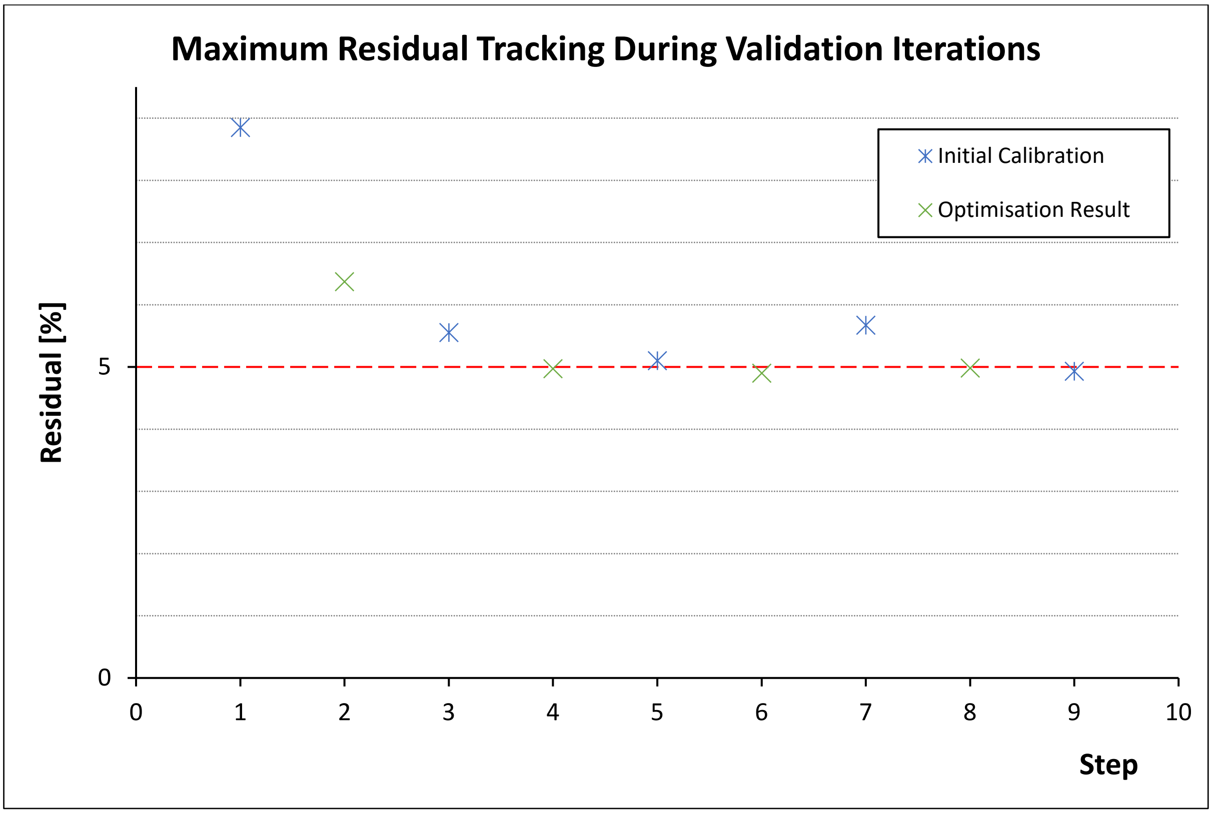

Figure 9 - Maximum Residual Error by Iteration

7 - Conclusions

The simulation results have shown that the proposed method of iterated between co-simulation and optimisation have progressively improved the calibration until it has met the desired MoS. It has also been demonstrated that, for the co-simulation model at least, it has been possible to meet the desired MoS of ±5% for all test points with a single optimised calibration. It is also interesting to note that as anecdotally experienced with manual calibration methods, the automated iterative process showed simulated results which were worse than the previous iteration due to the movement of the actual operating point of the engine for a pre-defined test point.

The automated optimisation demonstrated a theoretical reduction in the calibration validation time from 11 weeks to just 2 days on an engine dynamometer. This improvement comes from a combination of factors. Firstly, the automated procedure can be run on a 24-hour basis rather than being limited to supervised one or two shift testing. Secondly, the elimination of manual calibration changes significantly reduces the logistical delays of scheduling testing, expert analysis and re-testing as required on an ad-hoc basis. Finally, the automated optimiser developed by The Mathworks is significantly quicker than manual examination of the test data.

Finally, it should be noted that this paper demonstrates the process in a simulated environment which is not subject to experimental error, noise or other environmental factors which may affect the quality of the results. Therefore, actual turn-around time on the engine dynamometer may be slower, however this work has shown that it is likely to still be significantly more time-efficient than manual validation.

Further work on the VPEC project is continuing at Ford, who are currently working to automate the iterative optimisation process on their test cells. In addition to the on-going work to test the automated procedure on a dynamometer, further improvements have been proposed for the future. Firstly, it is possible to restrict the number of test points to be retested by examining the changes made by the optimiser. Therefore, only test points which will have been affected should be retested on subsequent iterations. Early results show that this can further reduce testing time by a factor of four or more. Secondly, the model has demonstrated substantial correlation to the test data especially under particular conditions. Therefore, a hybrid simulation/experimental validation method has been proposed to use a combination of simulated results and experimental results to allow the calibration to converge in fewer experimental iterations.

8 - References

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