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**Analytical Target Cascading Framework for Engine Calibration Optimisation**

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**Abstract:** This paper presents the development and implementation of an Analytical Target Cascading (ATC) Multi-disciplinary Design Optimisation (MDO) framework for the steady state engine calibration optimisation problem. The case is made that the MDO / ATC offers a convenient framework for the engine calibration optimisation problem based on steady state engine test data collected at specified engine speed / load points, which is naturally structured on 2 hierarchical levels: the "Global" level, associated with performance over a drive cycle, and "Local" level, relating to engine operation at each speed / load point. The case study of a gasoline engine equipped with variable camshaft timing (VCT) was considered to study the application of the ATC framework to a calibration optimisation problem. The paper describes the analysis and mathematical formulation of the VCT calibration optimisation as an ATC framework, and its Matlab implementation with gradient based and evolutionary optimisation algorithms. The results and performance of the ATC are discussed comparatively with the conventional two-stage approach to steady state calibration optimisation. The main conclusion from this research is that ATC offers a powerful and efficient approach for engine calibration optimisation, delivering better solutions at both "Global" and "Local" levels. Further advantages of the ATC framework is that it is flexible and scalable to the complexity of the calibration problem, and enables calibrator preference to be incorporated *a priori* in the optimisation problem formulation, delivering important time saving for the overall calibration development process.

*Keywords: Engine Calibration Optimisation, Multi-Disciplinary Optimisation, Analytical Target Cascading, Variable Valve Timing.*

## 1. Introduction

The development of engine technologies to improve performance, fuel economy and drivability while meeting increasingly stringent emissions legislation has resulted in an increased complexity of powertrain calibration with significant time and cost implications. With more engine actuators and controls to calibrate, the engine mapping and calibration task is significantly more involved and the task of identifying optimal actuator settings is much more difficult. To address the calibration challenges, Model Based Calibration (MBC) framework [1] is widely used to enhance the effectiveness of the engine calibration for both Diesel and modern gasoline engines using variable camshaft timing and direct injection.

The MBC framework for steady state engine mapping and calibration, illustrated in Figure 1 [2], is based on using efficient Design of Experiments (DoE) strategies to collect engine test data from steady state engine dynamometer testing facilities. Statistical models are fitted based on the collected steady-state engine test data to characterise the performance and emissions responses of the engine at each engine speed – load point. Optimal actuator setting at each engine speed / load point tested are then identified by applying optimisation techniques on the fitted engine response models. Smooth actuator maps are generated through interpolation based on the “local” (i.e. at each individual engine speed / load point) optimal solutions, and validated through further steady state and transient engine tests.

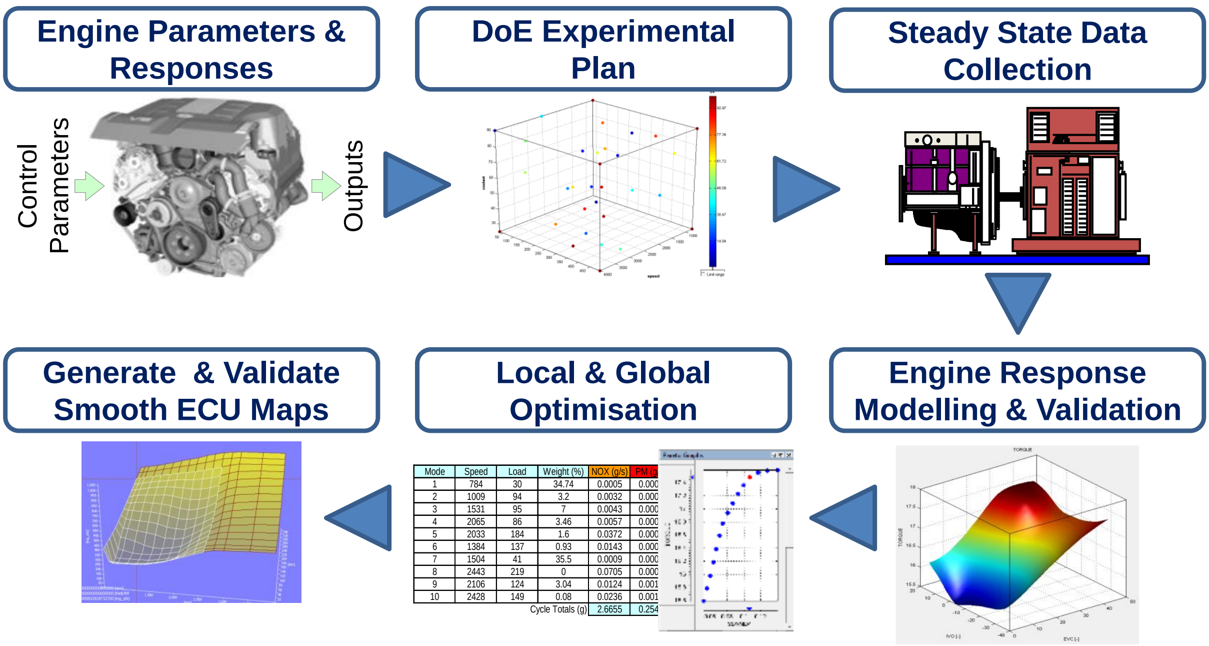



Figure 1: Model Based Calibration process

The complexity of optimisation problem for the steady state calibration arises from the implicit two-stage structure of the MBC process:

(i) "Local" optimisation – aiming to identify a set of "local" (i.e. at each engine speed / load point) optimal solutions that satisfy local objectives and constraints; the local problem is often defined as a "trade-off" optimisation between objectives, such as NOx and particulate emissions for a Diesel engine [1];

(ii) "Global" optimisation - which aims to identify a "global" (i.e. over the engine speed / load operating envelope) solution from the local optimal sets; generally, this is based on criteria associated with the overall targets for the engine or vehicle, such as overall fuel consumption and emissions over a specific drive cycle (e.g. NEDC emissions drive cycle).

Historically, the focus of optimisation methods development in MBC is often placed on the local optimisation task, aiming to implement efficient multi-objective algorithms to identify viable local trade-off solutions, usually based on a Pareto optimal set [3-5]. Identifying a global optimal solution for the engine calibration problem is often reduced to an exploratory search of local optimal solutions sets. Given the requirements to fulfil global objectives, such as fuel consumption and emissions over the drive cycle, but also to ensure that other engineering criteria are met by the calibration, such as the smoothness of the actuator maps linked to drive-ability attributes [6, 7], often results in difficulties with the global optimisation stage. This can be a very time consuming and iterative process, demanding calibration expertise in selecting a good set of global solutions, often requiring re-sampling from the local trade-off solutions set if global constraints cannot be met [6], and significant time and effort for the downstream calibration process. Attempts to address these difficulties have been based on either

(i) development of "global" response models [8], i.e. across the engine speed / load operating envelope, incorporating engine speed and engine load as variables; given the increasing number of calibratable variables, this approach could require extensive testing effort to generate models of sufficient quality to support optimisation;

(ii) combination of local and global optimisations in the same problem formulation; for example Roudenko [9] suggested a multi-objective optimisation formulation to minimise fuel consumption (global optimisation) and noise (local optimisation) under the constraints for global emissions ($NO_x$ and Soot) for a Diesel engine. However, the main shortcomings of this approach are the increase in the search space dimension, which reduces the computation efficiency.

This defines the need for better optimisation frameworks and strategies to handle the high dimensional calibration optimisation problem while addressing the complex couplings between system control variables. Multidisciplinary Design Optimisation (MDO) frameworks have been introduced as a more efficient approach for dealing with modern engineering systems with high dimensionality (more than 100 inputs variables) and strong coupling interactions, which are commonplace in modern aircraft and automotive vehicles [10, 11]. Solving such complex optimisation problems requires a methodology that can decrease the dimensionality, simplify / reduce the cost of the analysis while maintaining the consistency of the system [10]. MDO was described [11] as a methodology for the design of complex engineering systems that are governed by mutually interacting physical phenomena (subsystem or discipline) and made up of interacting subsystems or disciplines. MDO involves the development an engineering disciplinary decomposition to describe the interacting phenomena of the complex system. Several MDO approaches have been proposed to deal with practical problems of design optimisation of complex engineering systems; these include Individual- and Multiple - Discipline Feasible (IDF / MDF) [12], Collaborative Optimization (CO) [11], Bi-Level Integrated Synthesis (BLISS) [13], Concurrent Subspace Optimization (CSSO) [14] and Analytical Target Cascading (ATC) [10, 15-20].

Such approaches have been used for automotive applications, including engine optimisation [13], but not for calibration optimisation. A first study on the application of Collaborative Optimisation (MDO/CO) for the steady state Diesel engine calibration optimisation problem has been recently presented by Yin [6], showing that the MDO can offer clear advantages in terms of calibration optimisation problem formulation and quality of the solutions.

The idea proposed in this paper is to address the calibration optimisation problem in a holistic way by using an Analytical Target Cascading (ATC) MDO framework. This would enable the formulation of the calibration optimisation in a framework coherent with the hierarchy of "Global" and "Local" levels of optimisation tasks used by calibration engineers. A case study of a gasoline engine equipped with variable camshaft timing (VCT) will be considered to illustrate the implementation of the approach and evaluate its effectiveness compared to the traditional 2-stage optimisation approach.

The organisation of the paper is as follows: the next section presents a review of Multi-disciplinary Design Optimisation frameworks, focusing on the Analytical Target Cascading MDO approach. The research methodology, based on the VCT engine calibration optimisation problem, is discussed next, including the analysis of the calibration problem as MDO/ATC and its software implementation. Results from the implementation of the MDO/ATC framework for the engine calibration case study are presented comparatively with the conventional two-step optimisation approach, followed by a discussion of the results and the broader implication of this development for the steady state engine calibration optimisation.

## 2. Overview of Analytical Target Cascading

Analytical Target Cascading (ATC) is a multilevel MDO framework which has been developed to support optimal system design architectures associated with hierarchical partitioning into subsystems or sub-problems [16]. Typically, this partitioning based organisation of the problem matches the systems engineering design problem from a product development point of view. Figure 2 provides an automotive illustration of the function based hierarchical decomposition, where the utility function associated with the customer requirement (e.g. “torque demand”) is mapped to a functional requirement for the vehicle systems (e.g. powertrain – for which the main functional aim is to generate torque), which in turn is iteratively cascaded to the relevant subsystems (e.g. engine) and components (air and fuel intake and spark – for a gasoline engine). The system needs to be designed in a way that the customer demand is met at any time, which requires co-ordination of targets cascaded from the customer down through the system hierarchy to each component, as well as bottom-up re-balancing to ensure that subsystem requirements are met.

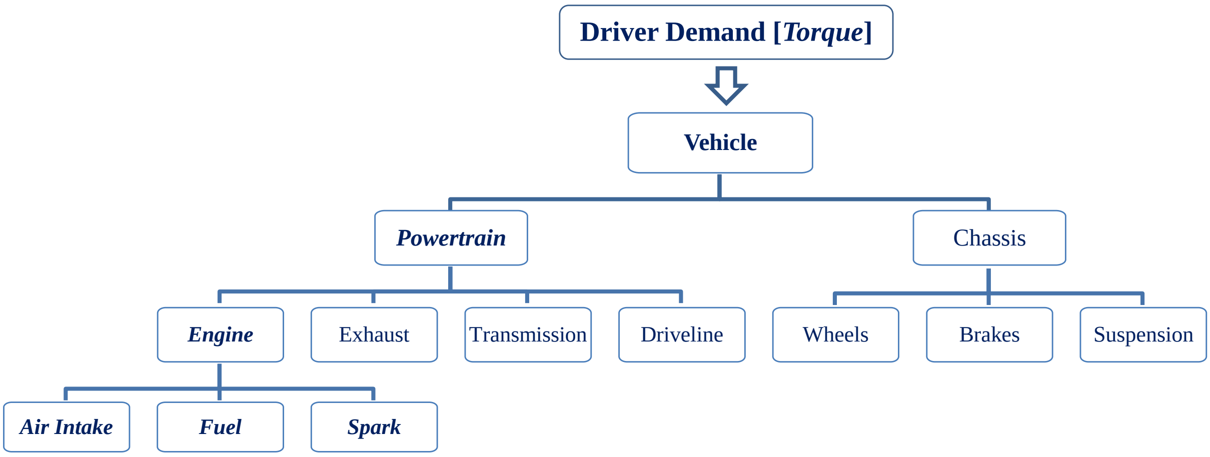



Figure 2: Illustration of Target Cascading in a vehicle systems engineering design

Figure 3 illustrates the functional hierarchy in the systems engineering cascade for the example in Figure 2, as well as a comparison between the conventional design optimisation problem formulation as "all-at-once" (AAO) [10] – on the left, and ATC – on the right. The main benefits of target cascading are the reduction in the analysis cost and time by decreasing the dimensionality of the optimisation problem (compared to all-at-once optimisation), and at the same time maintaining the whole system consistency through the rebalancing-up [15-17].

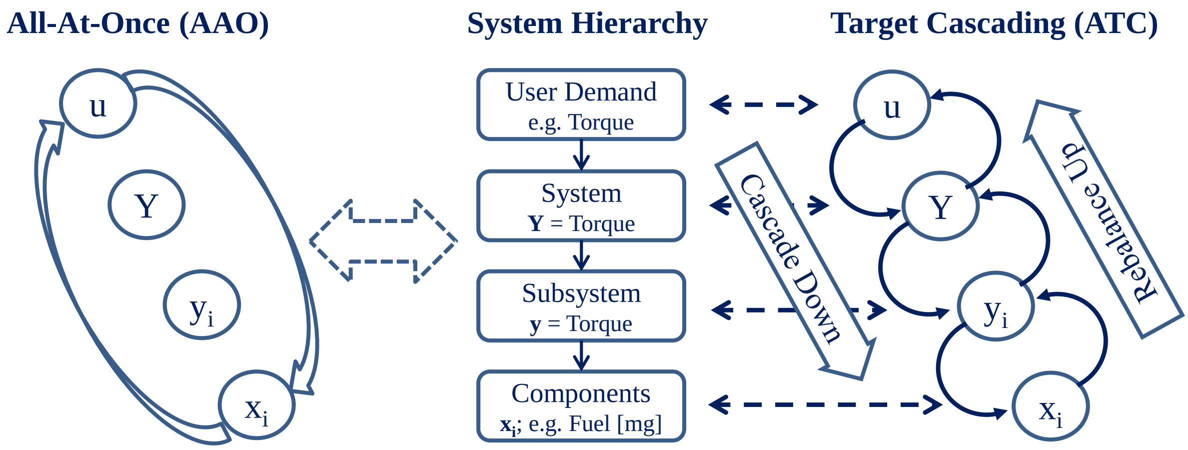



Figure 3: Illustration of AAO and ATC for a vehicle systems engineering design

The reader is referred to Kim et al. [19] and Kim [20] for a comprehensive mathematical description of the ATC framework. This section provides only a brief explanation of the target cascading process and the mathematical formulation of the optimisation problem, on the basis of a simplified generic system illustrated in Figure 4.

Within the ATC framework, distinction is made between optimal design levels (e.g. $P_{S1}$ for the system level, illustrated in Figure 4) and the analysis models (e.g. $\boldsymbol{Y_{s1}}$, which is a transfer function involving the system local variables $\boldsymbol{x_{s1}}$, linking (shared) variables $\boldsymbol{y_{s1}}$, and subsystems responses – $\boldsymbol{R_{ss1}}$ and $\boldsymbol{R_{ss2}}$, respectively). The targets for system level response value and linking variables $\boldsymbol{R_{s1}^{U}}$ and $\boldsymbol{y_{s1}^{U}}$ are cascaded down from the higher level system (e.g. vehicle level). After solving the system level optimisation problem, the system response values and linking variables $\boldsymbol{R_{s1}^{L}}$ and $\boldsymbol{y_{s1}^{L}}$ are returned to the vehicle level. Similarly, the design targets for responses and linking variables at each subsystem $\boldsymbol{i}$, $\boldsymbol{R_{ssi}^{U}}$ and $\boldsymbol{y_{ssi}^{U}}$, are passed down from the system level, and the solution of the subsystem level optimisation, $\boldsymbol{R_{ssi}^{L}}$ and $\boldsymbol{y_{ssi}^{L}}$, are returned to the system level [15-18].

At each level in the hierarchy, the ATC optimisation problem formulation can be formulated as minimisation of the discrepancy between the cascaded design targets and the returned responses, subject to system design constraints being satisfied. The optimisation formulation is shown in equation 1 for the system level illustrated in Figure 4 [15-20].

Objective: Minimise $\|R_{s1} - R_{s1}^{U}\| + \|y_{s1} - y_{s1}^{U}\| + \epsilon_R + \epsilon_y$

wrt $x_{s1}, y_{s1}, R_{ssi}, y_{ssi}, \epsilon_R, \epsilon_y$

Subject to:

$$\sum_k \|R_{ssk} - R_{ssk}^{L}\| \leq \epsilon_R$$

$$\sum_k \|y_{ssk} - y_{ssk}^{L}\| \leq \epsilon_y$$

$$g_{s1}(x_{s1}, y_{s1}, R_{s1}) \leq 0$$

$$h_{s1}(x_{s1}, y_{s1}, R_{s1}) = 0$$

$$x_{s1}^{min} \leq x_{s1} \leq x_{s1}^{max}\ ;\ \ y_{s1}^{min} \leq y_{s1} \leq y_{s1}^{max}$$ Equation 1

Where $\| \ \|$ denotes a metric for discrepancy between the target passed down and the system response calculated from the transfer function $Y_{s1}(x_{s1}, y_{s1}, R_{ss1}, R_{ss2})$, while $\varepsilon_R$ and $\varepsilon_y$ are deviation tolerances introduced to co-ordinate the sub-system level responses (as discrepancy between the target passed down and the response from the lower subsystem), and $g_{s1}$ and $h_{s1}$ are inequality and equality constraints, respectively, imposed at the system level. The ATC cascade starts at the highest level of the system with a target, T, so the first optimisation is with respect to the discrepancy between the response and the target, i.e. $\|R_{s0} - T\|$. However, modified approaches have been discussed in literature [21] in which the ATC cascade is not necessarily started with a specified target, reflecting product development situations where a design target is not necessarily known a priori. In such situations, the system level response is minimised at the top-level of the hierarchy (or system level) and the solution is cascaded down to the lower levels as the target.

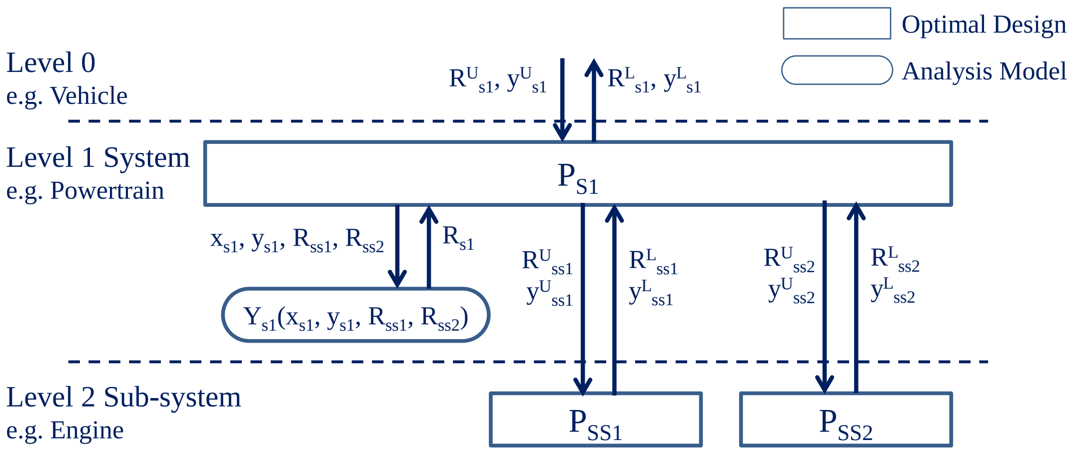



Figure 4: Illustration of ATC flow of information

The main difference between ATC and other MDO approaches is the multi-level structure and the focus on both targets and system variables. For example, in Collaborative Optimisation (MDO/CO) the original problem is decomposed into a bi-level structure, system level and subsystem level, and a coordination problem is defined at the top level of the hierarchy. The discrepancies between the interaction (or interdisciplinary) variables and targets are minimised at the subsystems. In this approach, the constraints of the original problem are distributed to the subsystems and the subsystem level objective is defined as an equality constraint at the system level [15-18]. The main drawback of this process is that the whole system consistency is often endangered if the subsystem level returns a significantly different solution for the interdisciplinary variables [17]. Moreover, no convergent coordination strategy is defined to enable decomposition to more than two levels (bi-level). As discussed, in the MDO/ATC framework, the system level and subsystems are decoupled by applying a deviation penalty function at all levels, which solves the problem of convergence in multi-level approaches and also gives the opportunity to decompose the original problem into more than two levels [15-17].

## 3. Research Methodology

The research aim of this study was to evaluate the applicability and effectiveness of a MDO/ATC type framework for an engine calibration optimisation problem. To this end, a case study approach was considered, where a calibration optimisation problem can be analysed within an ATC framework, followed by implementation and evaluation of the results against a set benchmark.

### 3.1. Case Study: Variable Valve Timing Calibration for a Gasoline Engine

For the purpose of this work a case study originally presented by Singh [4, 22] for the calibration of a port-fuel injection gasoline engine equipped with variable camshaft timing was considered. Modern engines use Variable Camshaft Timing (VCT) control strategies at part throttle in order to achieve fuel economy and emissions benefits. Variable cam timing involves phase-shifting the camshaft(s) relative to crankshaft as a function of engine operating conditions. For an engine equipped with VCT, the calibration optimisation task is to identify optimal settings for the camshaft timing variables, e.g. timing for the injection valve opening (IVO) and exhaust valve closing (EVC) events, such that the benefits of the VCT technology (reduced emissions, improved fuel economy and power) are optimally achieved. This would normally require a large amount of testing in addition to the base calibration of the engine. The original Case Study used a Model Based Calibration approach, coherent with the framework illustrated in Figure 1, and employed a 2-stage optimisation process to derive an optimal calibration. While the original aim of the case study [4, 22] was to evaluate different camshaft control strategies (twin-independent Versus intake- or exhaust-only Versus the "fixed timing" benchmark), in this work we will concentrate on the optimisation problem formulation for the twin independent camshaft valve timing control case, comparing the results against the 2-stage optimisation process and the "fixed timing" benchmark.

The engine Case Study test data was collected at 9 engine speed (N) engine load (MAF) points, representing part throttle operation, summarised in Table 1. The load setting (MAF) was the fraction of the maximum cylinder air charge possible at a given RPM based on measured airflow [4, 22]. At each engine speed / load point, engine test data was collected based on a DoE plan consisting of a 20 runs V-Optimal design based on a third order polynomial, augmented with 4 additional runs to minimise the prediction error variance (PEV). Five additional test points were collected to provide an external model validation data set. Table 2 summarises the variables (and range for each variable) considered in the experiment, i.e. IVO and EVC, in degrees of crank angle measured from the Top Dead Centre (TDC). The engine responses of interest for this study collected at each experimental run included *Torque* output from the engine, [Nm]; *NOx* emissions, [g/hr]; *NMEP* – Net indicated Mean Effective Pressure, [bar]; *SDNMEP* – Standard Deviation of NMEP, [bar], taken as measure of the combustion stability of engine; *MAP* – Manifold Absolute Pressure, i.e. the pressure at inlet manifold, [bar].

Table 1: Engine steady state testing points

| **MAF/N** | **1000** | **2000** | **3000** |
|---|---|---|---|
| **100** | 1 | 4 | 7 |
| **150** | 2 | 5 | 8 |
| **200** | 3 | 6 | 9 |

Table 2: Calibration factors and design space

| **Control Variable / DoE Factor** | Min | Max |
|---|---|---|
| Intake Valve Opening Event (IVO) | -36 | 14 |
| Exhaust Valve Closing Event (EVC) | 0 | 45 |

Response surface models were generated for each response as a function of the camshaft timing variables (EVC, IVO) using the Model Browser tool in the Model Based Calibration (MBC) Matlab toolbox. While the original analysis of this data [4, 22] considered only third order cubic polynomial models, for the purpose of generality of the optimisation implementation, recognising that most engine testing is currently conducted multi-level space-filling designs [7], Radial Basis Function (RBF) models [23] were fitted. Model selection was based on minimisation of PRESS-RMSE (Prediction Sum of Squares –Root Mean Squared Error) [24]. The models were validated based on statistical criteria, i.e. PRESS-RMSE and validation RMSE (calculated from the prediction errors for the external validation set), as well as engineering judgement through analysis and validation of engineering trends. For illustration of the latter method, Figures 5 and 6 show the response surfaces fitted for Torque and SDNMEP at operating point 1, corresponding to a low speed – low load setting (test point 1). Figure 5 shows that torque reaches maximum either when both IVO and EVC are retarded (i.e. “dual retard”, Region 1), or when the inlet valve opens early while the EVC is retarded (i.e. “maximum overlap”, Region 2). These results are consistent with engineering expectation; e.g. for “dual retard” pumping work is reduced due to increased exhaust residuals (which increases the cylinder pressure) and this requires an increase in the throttle to maintain the same load [25], hence more output torque is produced. Similarly, at the “maximum overlap” setting, the in-cylinder pressure is increased which means more work is done on the piston during the induction stroke, therefore, less work is needed for pumping the fresh air into cylinders. However, Figure 6 shows that SDNMEP, which is taken as a measure of combustion stability, is high in the “maximum overlap” area, due to reduction in flame speed and burn rate [26].

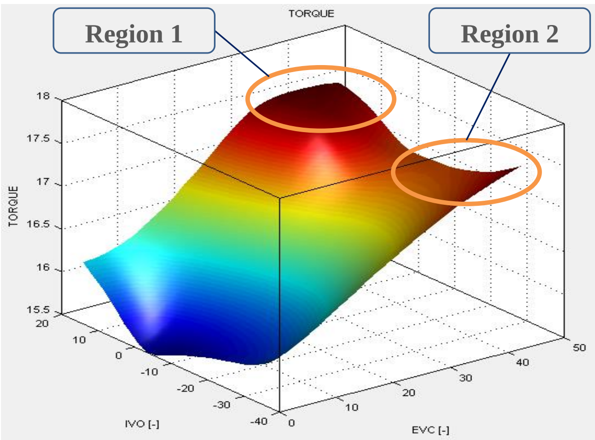



Figure 5: Torque response surface – RBF model for 1000 RPM/100 MAF

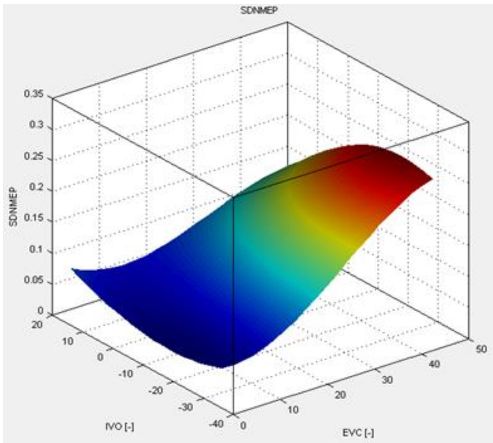



Figure 6: SDNMEP response surface - RBF Model for 1000 RPM/100MAF

### 3.2. VCT Calibration Optimisation Problem Analysis

As discussed, using VCT controls enables to vary the valve event timings across the engine operating points (i.e. engine speed – load) to deliver specific fuel economy or emissions benefits. This defines a need for “local” optimisation at each engine speed – load point to identify optimal settings. For example, with reference to the response graphs illustrated in

Figures 5 and 6, there is a clear need for a trade-off analysis as the setting that maximizes torque (region 2) has unacceptably high SDNMEP, hence poor combustion stability. A typical multi-objective trade-off optimisation formulation for the VCT "local level" optimisation is shown in equation 2.

*Maximize* Torque (IVO, EVC) [Nm]
*Minimize* SDNMEP (IVO, EVC) [bar]

*Subject to*:
*Linear constraints:* $-36 \le \text{IVO} \le 14$ [deg ATDC];
$0 \le \text{EVC} \le 45$ [deg ATDC];
*Non- linear constraints:* SDNMEP (IVO, EVC) $\le 0.2$ bar

Equation 2

From an engineering point of view, a threshold for SDNMEP is usually imposed to define the feasible area for the combustion stability, e.g. SDNMEP $\le 0.2$, as shown in equation 2. The aim of this local trade-off optimisation is to identify more robust calibration solutions that deliver the torque advantage with good combustion stability. The study reported by Singh et al [4] argued that a multi-evolutionary approach based on the NSGA-2 algorithm [27] delivers superior results for the local trade-off optimisation.

However, solving the local optimisation problems would not necessarily result in a calibration schedule that is acceptable overall, i.e. across the engine speed / load operating range. This is for 2 reasons:

(i) The overall calibration requirement is usually focused on "global" performance criteria such as fuel economy and emissions over a drive cycle (e.g. the NEDC emissions drive cycle); the chosen set of optimal local solutions might not deliver the best "global" optimum.

(ii) As discussed in [4], if the "global" calibration solution involves a large change in either IVO or EVC timing with a swift load increase, such a solution would be unacceptable, because it could result in customer perceived transient drive-ability issues, and it could negatively affect the reliability of the VCT hardware.

If the set of chosen local optimal solutions does not satisfy the global optimisation requirements, the calibration engineer has the option to re-sample from the local Pareto sets. This can lead to an iterative process which can be very time consuming, and arguably still not delivering the best overall solution.

Singh et al [4] have discussed a global optimisation strategy based on narrowing the variables domain, defining 2 strategies for twin independent camshaft timing control:

1. *Dual retard*: where both camshaft timings events are retarded into the intake stroke, i.e. $-11 \leq \text{IVO} \leq 14$ [deg ATDC];   $22.5 \leq \text{EVC} \leq 45$ [deg ATDC]
2. *Maximum overlap*: early IVO timing ($-36 \leq \text{IVO} \leq -11$ [deg ATDC]) and retarded EVC ($22.5 \leq \text{EVC} \leq 45$ [deg ATDC]), resulting in a maximum overlap between the opening of the inlet valve and the exhaust valve closing.

Both of the above strategies have been discussed [4] as being effective at reducing the intake pumping loss, and hence delivering torque and/or fuel consumption benefits, as well as emissions reduction. Constraining the solution domain as defined above in effect limits the maximum actuator change between engine speed-load points, thus ensuring a smooth actuator map. The global optimisation problem corresponding to this analysis can be written mathematically as in equation 3.

*Minimize* Fuel Consumption (IVO, EVC)

Subject to:

*Linear constraints:*

*Max Overlap:* $-36 \leq \text{IVO} \leq -11$ [deg ATDC]; $22 \leq \text{EVC} \leq 45$ [deg ATDC]

*Dual retard:* $-11 \leq \text{IVO} \leq 14$ [deg ATDC]; $22 \leq \text{EVC} \leq 45$ [deg ATDC]

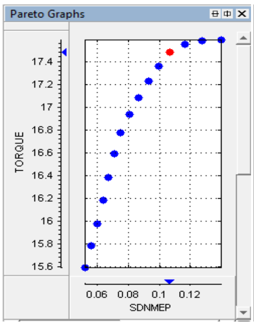
*Non- linear constraints:*

NOx (IVO, EVC) $\leq$ Limit [gr/km]

Equation 3

The Matlab Model Based Calibration (MBC) toolbox offers a convenient environment for carrying out calibration optimisation in a 2-stage process. With reference to the Case Study, the engine response models fitted to the test data using the Model Browser MBC tool were exported to the Calibration Generation (CaGe) MBC tool, which can manage both the local and the global optimisation steps. Figure 7 illustrates a CaGe output for the local trade-off optimisation (at test point 1 - 1000 RPM / 100 MAF), showing both the graphical illustration of the Pareto frontier and the table of solutions on the Pareto front. The multi-objective algorithm available in CaGe is NBI (Normal Boundary Intercept), which has the advantage of being fast; however, it is susceptible to fall in local optimum syncs [28]. It is therefore essential that the optimisation is started from several guess points – which will in fact generate multiple Pareto fronts, from which solutions can be selected. Following this process, trade-off optimisations were carried out at all 9 test points. Figure 8 illustrates the chosen global "best" solution (in the actuator space), obtained through an exploratory search of candidate solutions from the "local" Pareto "candidate" sets. This shows an acceptable solution from a calibration point of view, corresponding to a "Dual retard" strategy. Compared to the fixed timing (IVO = -6°; EVC = 6°) benchmark, the calibration illustrated in Figure 8 delivers a drive cycle average enhancement in Brake Specific Fuel Consumption (BSFC, equation 4, calculated at each engine speed / load point based on the assumption of stoichiometric engine operation) of 5.76% and a reduction in NOx of 62.67% (calculated on the assumption of an equal weight, $w_i$ = 1/9, of points in a virtual drive-cycle). This solution is similar to the result reported by Singh et al [4] in the original analysis of this case study data, derived from using cubic polynomials for the engine response models and NSGA2 trade-off local optimisation algorithm.

$$F_s = \sum_i w_i \cdot BSFC(IVO_i, EVC_i), \quad i = 1..9 \qquad \text{Equation 4}$$




| Solution | | Accept | IVO | EVC | TORQUE | SDNMEP |
|---|---|---|---|---|---|---|
| 1 | | ✓ | -7.173 | 3.673 | 15.595 | 0.052 |
| 2 | | ✓ | -7.908 | 7.908 | 15.781 | 0.056 |
| 3 | | ✓ | 1.816 | 8.258 | 15.976 | 0.06 |
| 4 | | ✓ | 5.773 | 9.705 | 16.181 | 0.064 |
| 5 | | ✓ | 9.499 | 11.523 | 16.385 | 0.067 |
| 6 | | ✓ | 13.354 | 13.787 | 16.589 | 0.071 |
| 7 | | ✓ | 14 | 17.118 | 16.776 | 0.075 |
| 8 | | ✓ | 14 | 19.93 | 16.937 | 0.081 |
| 9 | | ✓ | 14 | 22.417 | 17.086 | 0.087 |
| 10 | | ✓ | 14 | 24.746 | 17.227 | 0.093 |
| 11 | | ✓ | 14 | 27.03 | 17.36 | 0.1 |
| 12 | | ✓ | 14 | 29.449 | 17.479 | 0.107 |
| 13 | | ✓ | 13.947 | 32.507 | 17.552 | 0.116 |
| 14 | | ✓ | 12.118 | 34.254 | 17.583 | 0.128 |
| 15 | | ✓ | 10.652 | 36.474 | 17.594 | 0.14 |

Figure 7: Illustration of trade-off optimisation in Matlab CaGe for Torque and SDNMEP for test point 1 (1000 RPM/100 MAF)

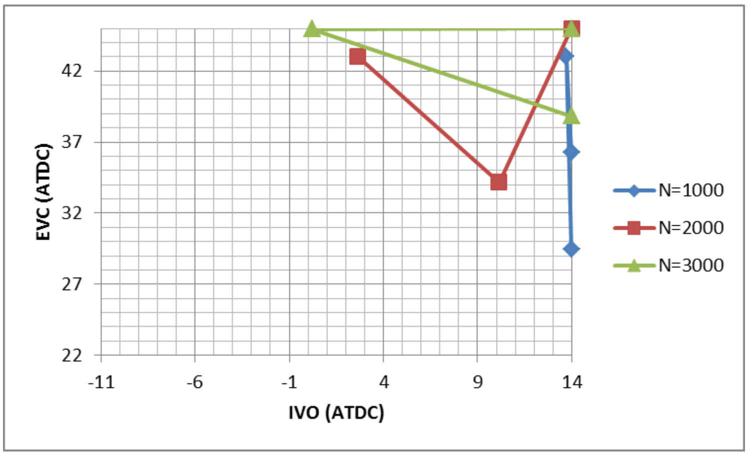



Figure 8: Illustration of optimal calibration solution from the 2-stage calibration process

The major shortcoming of this approach to VCT calibration optimisation comes from the nature of the two-stage process, which is time consuming, requires calibration expertise input in the evaluation and selection of the trade-off solutions, and it could require a number of iterations (where the local optimisation needs to be re-run in order to generate more / additional trade-off points) until an acceptable global solution can be reached. It can also be argued that the global level optimisation is not goal focused: it does not actually minimise fuel economy or emissions; instead, the global solution is the best combination of the local trade-off solutions, which have not been selected for their potential contribution to overall fuel consumption or NOx improvement.

In order to deliver a better approach to solve the VCT calibration optimisation problem, the 2 optimisation sub-problems ("Local" and "Global") should ideally be approached and solved concurrently, such that both over the drive cycle benefits (fuel consumption and emissions, i.e. global objectives) and local benefits (i.e. torque enhancement at each engine speed / load operating point) are achieved.

## 3.3. ATC Framework for Calibration Optimisation

### 3.3.1. Analysis of VCT Calibration Optimisation Problem as ATC

As discussed, the VCT calibration optimisation problem is naturally structured on 2 levels: the "Global" level, which relates to engine performance over the drive cycle, and the "Local" level, associated with the individual points in the engine speed – engine load space, where local performance needs to be optimised. A 2-level MDO / ATC framework can be associated with the engine calibration problem, by treating each calibration point as a subsystem or discipline, and the "Global" – over the drive cycle performance being the system optimisation problem.

Figure 9 illustrates the organisation of the VCT problem as ATC. The overall objective of the calibration optimisation problem is to find optimal solutions for the calibration variables ($y_s^U$) (i.e. IVO and EVC settings) to achieve the system target ($F_s^U$). The overall main objective of the calibration is to minimise fuel consumption, so the system target ($F_s^U$) can be defined in relation to BSFC over the drive cycle, given by equation 4.

The optimisation problem at system level, shown in Figure 9, is similar to the general ATC formulation defined in equation 1. The calibration variables are in this case the linking variables $y_s$, and the deviation tolerances $\epsilon_y$ defines the allowable discrepancy between the system level and subsystem level solutions. It is noteworthy that in this case the subsystems share their variables ($y_{ssi} = \begin{bmatrix} IVO_{ssi} \\ EVC_{ssi} \end{bmatrix}$) with the system level, but there is no direct coupling between subsystems as they do not share any of the variables. The deviation tolerance $\epsilon_F$ defines the allowable discrepancy between the system target for BSFC and the subsystems solutions.

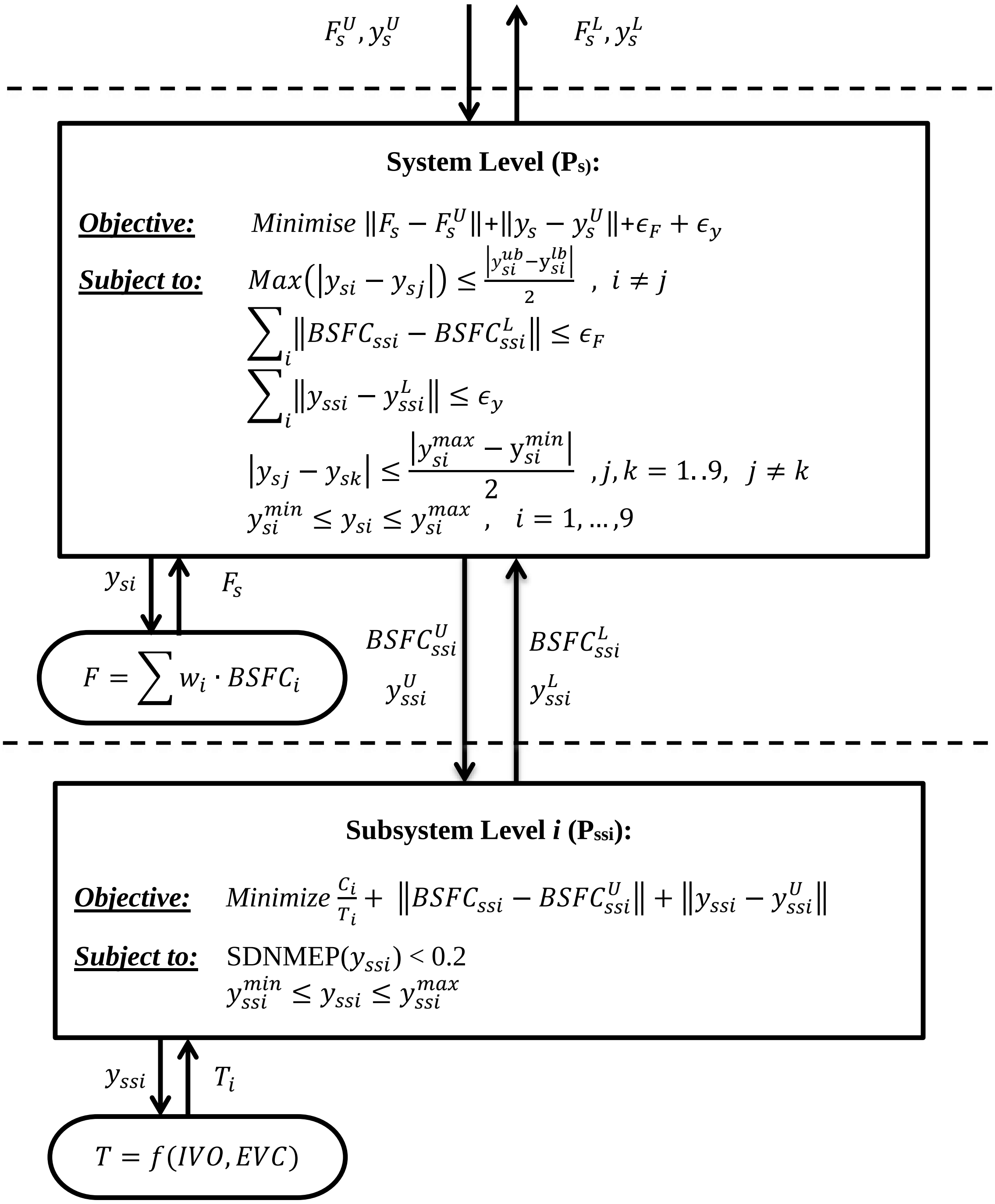



Figure 9: VCT calibration optimisation problem as MDO/ATC

The engineering requirement for a smooth actuator map was introduced as a nonlinear constraint between the linking variables at the system level, equation 5. In effect this constraints the maximum actuator change related to any transition between any 2 points *j* and *k* to half the design space (defined in Table 2) – which is a strategy similar to the one adopted by Singh et al [4] based on calibration engineering consideration.

$$\left|y_{sj} - y_{sk}\right| \leq \frac{\left|y_{si}^{max} - y_{si}^{min}\right|}{2} \ , \ j \neq k \qquad \text{Equation 5}$$

At the **subsystems level**, the main objective for each subsystem $i$ (i.e. at each engine speed / load point) was defined to maximize torque ($T_i$) for the given air flow, while meeting combustion stability engineering criteria (SDNMEP < 0.2 threshold) and ensuring consistency with the system level targets for main objective function and linking variables (i.e. minimise discrepancy between subsystem solutions and system targets). Mathematically, this was formulated as a minimisation problem, as shown in Figure 9, by considering a normalised transformation of the torque function, $(C_i/T_i)$. For each local point $i$, the normalising constant $C_i$ was considered to be the *maximum torque* achievable by varying the calibration variables within the domain space.

### 3.3.2. ATC Framework for VCT Optimisation: Implementation

The implementation of the ATC formulation of the VCT calibration problem illustrated in Figure 9 was done in Matlab. This enabled to utilise the RBF response surface models fitted by using the MBC Model Browser tool, exported as data structures in the Matlab environment, and utilised in conjunction with several optimisation algorithms.

The implementation of the ATC framework presented in Figure 9 required several auxiliary optimisation problems to be resolved first:

(1) The **system target** ($F_S^U$): No target for overall BSFC (over the virtual drive cycle) was available, therefore, similar to the approach described in [21], the solutions from the unconstrained optimisation of BSFC over the range of calibration variables (equation 6) were considered instead. A global optimisation algorithm (the standard Genetic Algorithm (GA) available in the Matlab Global Optimisation toolbox) was employed to derive values for $F_S^U$ and $y_S^U$ – to be used as targets for the ATC implementation.

$$\begin{aligned}
&\textit{Minimize } \textstyle\sum_i BSFC(IVO_i, EVC_i)\ , \quad i = 1, \dots, 9 \\
&\textit{Subject to:} \\
&\quad \textit{Linear constraints:} \quad -36 \le IVO_i \le 14 \ [deg\ ATDC]; \\
&\qquad\qquad\qquad\qquad\qquad\quad 0 \le EVC_i \le 45 \ [deg\ ATDC];
\end{aligned} \qquad \text{Equation 6}$$

(2) The **subsystems constants for torque normalisation**: For each local point *i* the value of the normalising constant $C_i$ was defined as the *maximum torque* achievable by varying the calibration variables within the domain space. A global optimisation algorithm (the Matlab GA) was used to derive the constants $C_i$ by solving the optimisation problem described in equation 7.

$$\begin{aligned}
&\textit{Minimize } -T(IVO_i, EVC_i) \\
&\textit{Subject to:} \\
&\quad \textit{Linear constraints:} \quad -36 \le \mathrm{IVO_i} \le 14 \ [\mathrm{deg\ ATDC}]; \\
&\qquad\qquad\qquad\qquad\qquad\quad 0 \le \mathrm{EVC_i} \le 45 \ [\mathrm{deg\ ATDC}];
\end{aligned} \qquad \text{Equation 7}$$

For the implementation of the ATC framework we need to consider the selection of appropriate optimisation algorithms for both system and subsystem problems illustrated in Figure 9. The subsystem level involves the concurrent solving of *n* optimisation problems corresponding to the defined subsystems (*n = 9* in this case). A fast gradient based algorithm is required for this task, therefore the *fmincon* Matlab function, which is based on a sequential quadratic programming (SQP) algorithm, was chosen. The susceptibility of the gradient based search to be trapped in a local optimum is an advantage for the subsystem optimisation because it favours solutions close to the system target.

For the ATC system level optimisation either gradient based or global optimisation algorithms can be employed. Given that the system optimisation problem is based on response surface models, gradient based algorithms, such as Matlab *fmincon*, can be employed and can be expected to lead to a fast convergence. The argument for employing a global algorithm for the system level optimisation in an MDO engine calibration optimisation problem has been made by Yin [6] on the basis that a population based search would provide a better exploration of a heavily constrained design space, with the potential to yield better solutions for the calibration problem. In order to evaluate the performance of global search algorithms against a gradient based algorithm (Matlab *fmincon*) for the VCT calibration problem, two Matlab global optimisation algorithms were considered:

1) Genetic Algorithm, based on the standard Matlab GA implementation provided in the Global Optimisation toolbox;
2) Particle Swarm Optimisation (PSO), based on a custom Matlab implementation of the PSO algorithm described in [29].

In order to facilitate the convergence in standard ATC frameworks, Allison et al. [30] proposed the introduction of penalty terms to change the weight of discrepancy terms in the system level and subsystem level objective functions. Therefore, the formulation of discrepancy terms in the system level and subsystem level objective functions were revised as shown in equations 8 and 9, respectively. The values of penalty terms vary at each optimisation iteration through the change in the discrepancy between the system level and subsystem level solutions, shown in equation 10.

**At system level:**

$$\|F_s - F_s^U\| = \sum_i v_{Fi}|F_s - F_s^U| \times u_i\,(F_s - F_s^U)^2$$

$$\|y_s - y_s^U\| = \sum_i v_{yi}|y_s - y_s^U| \times u_i\,(y_s - y_s^U)^2$$

Equation 8

**At subsystem level:**

$$\left\|BSFC_{ssi} - BSFC_{ssi}^U\right\| = v_{Fi}\left|BSFC_{ssi} - BSFC_{ssi}^U\right| \times u_i(BSFC_{ssi} - BSFC_{ssi}^U)^2$$

$$\left\|y_{ssi} - y_{ssi}^U\right\| = v_{yi}\left|y_{ssi} - y_{ssi}^U\right| \times w_i(y_{ssi} - y_{ssi}^U)^2$$

Equation 9

**Penalty Terms:**

$$v_{F(i+1)} = v_{Fi} + 2 \times u_i{}^2 \times \left|BSFC_{ssi}^U - BSFC_{ssi}^L\right|$$

$$v_{y(i+1)} = v_{yi} + 2 \times u_i{}^2 \times \left|y_{ssi}^U - y_{ssi}^L\right|$$

$$u_{i+1} = B \times u_i$$

Equation 10

where $v_{Fi}$ and $v_{yi}$ are adaptive penalty functions at each iteration, and *B* and *u* are constant coefficients, chosen to ensure a smooth convergence to the optimum solutions [30]. For the VCT optimisation problem the values chosen for the coefficients were $u_1$=*1*, *B = 1.3,* and $\epsilon_F$ and $\epsilon_y$ were *0.01*.

### 3.3.3. ATC Framework: Results

Figures 10 – 12 illustrate convergence plots for the ATC optimisation with different optimisation algorithms at the system level, showing a consistent optimisation process and convergence in all cases. Table 3 summarises the optimal calibration solutions for each of the 9 local points. The data in Table 3 shows that the all 3 ATC optimisation algorithms have converged to a very similar solution, illustrated graphically in Figure 13 in the solution space (IVO / EVC co-ordinates). This is an acceptable calibration solution corresponding to a "dual retard" strategy, similar to the 2-stage solution chosen based on calibrator input. Comparing Figures 8 (2-stage solution) and 13 (ATC) it is apparent that the ATC solution is a "smoother" calibration based on the smaller range of actuator change.

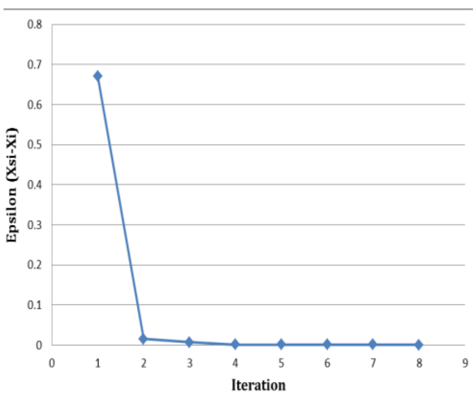



Figure 10: Convergence plot for *fmincon* (based on the discrepancy between system level and subsystem level solutions)

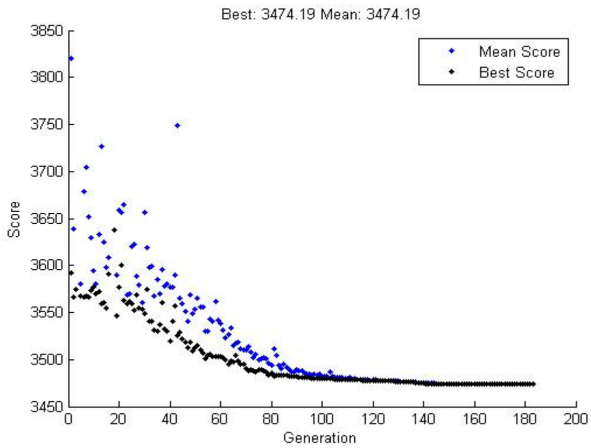



Figure 11: Convergence plot for PSO (based on fitness function)

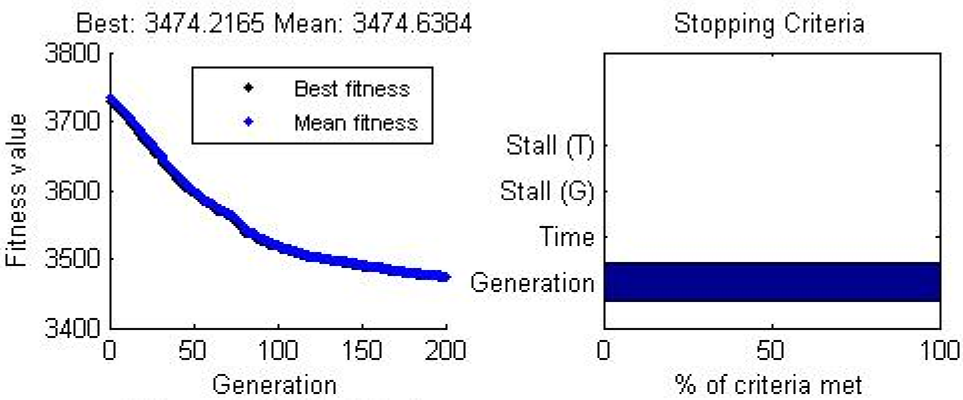



Figure 12: Convergence plot for GA (based on fitness function)

Table 3: ATC Calibration optimal solutions

| **Global Optimisation** | | **fmincon** | | **GA** | | **PSO** | | ***2-Stage Solution*** | |
|---|---|---|---|---|---|---|---|---|---|
| **Speed** [rpm] | **Load** [MAF] | IVO [°ATDC] | EVC [°ATDC] | IVO [°ATDC] | EVC [°ATDC] | IVO [°ATDC] | EVC [°ATDC] | IVO [°ATDC] | EVC [°ATDC] |
| **1000** | **100** | 12.36 | 40.85 | 13.01 | 41.12 | 12.54 | 41.42 | *14* | *29.45* |
| **1000** | **150** | 2.31 | 45 | 3.27 | 45 | 2.35 | 45 | *13.7* | *43* |
| **1000** | **200** | 14 | 45 | 14 | 45 | 14 | 45 | *14* | *36.3* |
| **2000** | **100** | 14 | 45 | 14 | 45 | 14 | 45 | *14* | *45* |
| **2000** | **150** | 8.07 | 45 | 10.05 | 45 | 9.32 | 45 | *10.14* | *34.15* |
| **2000** | **200** | 9.15 | 43.97 | 8.97 | 44.08 | 10.16 | 44.21 | *2.65* | *43* |
| **3000** | **100** | 14 | 45 | 14 | 45 | 14 | 45 | *14* | *45* |
| **3000** | **150** | 10.34 | 42.35 | 11.15 | 43.02 | 10.88 | 42.89 | *0.23* | *44.97* |
| **3000** | **200** | 14 | 44.97 | 14 | 45 | 14 | 45 | *14* | *38.84* |

Table 4 provides a comparison of the performance of the ATC optimisation versus the 2-stage calibration process, expressed in terms of percentage improvement over the fixed cam timing benchmark (IVO = -6°; EVC = 6°) for torque (calculated as average torque improvement over the 9 points), drive cycle BSFC (assuming equal weight of the points in the drive cycle, i.e. $w_i = 1/9$), and reduction in NOx over the drive cycle. The results in Table 4 show that the ATC optimisation clearly outperforms the 2-stage calibration approach, delivering significant improvements both at local level – in terms of torque, and at global level – BSFC and NOx. The 3 algorithms employed in the ATC system level optimisation showed similar performance in terms of objectives, however, the fmincon is much faster compared with the population based algorithms (GA and PSO).

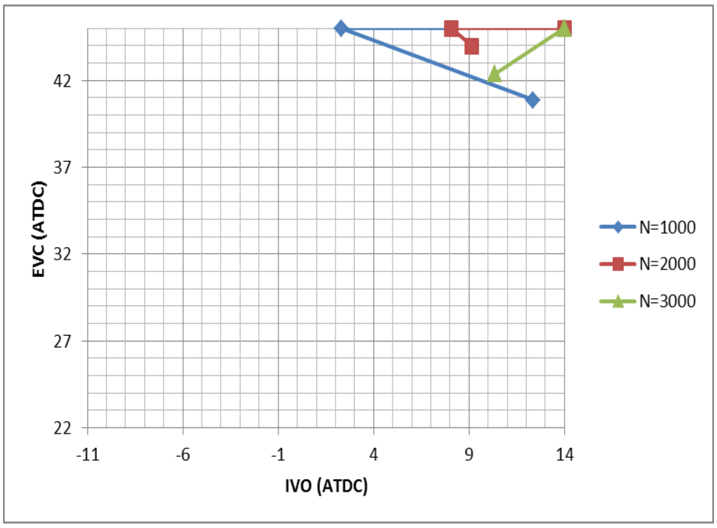



Figure 13: ATC approach, calibration optimal solution in the Actuator Space

Table 4: Comparison of ATC algorithms performance [% improvement over benchmark]

| Optimisation Algorithm | Torque [% Improvement] | BSFC [% Improvement] | NOx [% Improvement] | Duration [Sec] |
|---|---|---|---|---|
| *Two-Stage* | *6.27* | *5.76* | *62.67* | --- |
| ATC (fmincon) | 6.897 | 6.4 | 68.33 | *35* |
| ATC (ga) | 6.905 | 6.41 | 68.11 | *3896* |
| ATC (pso) | 6.9 | 6.404 | 68.42 | *2268* |

**4- Discussion and Conclusion**

This paper has demonstrated that the ATC MDO framework can deliver strong benefits for the steady state engine calibration optimisation problems. Given the structure of the steady state calibration problem which involves at least 2 hierarchical levels, the MDO approaches offer a natural framework for optimisation problem formulation. A particular feature of the decomposition of the steady state calibration optimisation problem is that there is no direct coupling between "local" variables (given that the engine operating points are treated as independent operating states, the variables associated with each state – i.e. actuator settings, can be assumed to be independent), and that the "subsystems" share all their variables with the "system". This can be regarded as a strict hierarchical decomposition, suggesting that the ATC should be the MDO framework of choice, based on its strength in ensuring a convergent co-ordination strategy. This has been demonstrated through the application of the ATC framework to the VCT calibration problem.

The advantages of the ATC framework can be summarised as follows:

- The case study analysis has demonstrated that the ATC framework outperforms the 2-stage calibration approach in terms of performance / quality for both the overall (over the drive cycle) calibration results and the local solutions. Thus, the ATC framework addresses the weakness of the 2-stage process that it is not "goal" focused on the global calibration objective. Given that the ATC optimisation can be very fast, in particular when a gradient based optimisation algorithm is employed at the "system" level, the ATC also offers a strong alternative to the current calibration optimisation platform available in Matlab CaGe.
- The ATC framework allows for calibration engineering preferences to be included in the optimisation problem formulation, removing the need for calibrator input in the optimisation process. This has been illustrated in the VCT calibration case study by incorporating the calibration preference for a "smooth actuator map" through the

formulation of a constraint on the maximum actuator change. The results have comprehensively demonstrated the effectiveness of the ATC approach, which returned a calibration solution corresponding to the “dual retard” strategy, with no need for a separate evaluation study as conducted in the original case study analysis by Singh [4].

- The ATC framework is scalable – it can be flexibly extended accommodate any number of local calibration points. The framework could also allow a multi-level decomposition, e.g. to support base calibration for different modes of operation of the engine, such as “cold” calibration and “hot” calibration, while meeting the overall target for fuel consumption and emissions.
- The ATC MDO frameworks offer the opportunity to integrate the calibration optimisation problem with the higher levels of the systems engineering hierarchy, e.g. powertrain and vehicle system optimisation. This is important as it would enable co-development of calibration and subsystem level design; e.g. calibration optimisation could be combined with the aftertreatment and driveline system optimisation, co-ordinated by the powertrain system targets.

One limitation of this study is that the dimensionality of the VCT calibration problem was small compared to that of developing a base calibration for the full engine speed / load space for a gasoline or diesel engine. Such problems would normally involve 6-12 calibratable variables, with 10 – 30 (or even more) points where steady state testing is conducted, and more complex constraints for the calibration. While the MDO / ATC framework is flexible and scalable – so it can easily accommodate problems with large dimensionality, such as that discussed by Yin [6], further research is needed to validate the robustness and relative effectiveness of different optimisation algorithms, in particular for the system level optimisation in the ATC framework.

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**List of Notations:**

ATC: Analytical Target Cascading

BSFC: Brake Specific Fuel Consumption

CO: Collaborative Optimisation

DoE: Design of Experiment

ECU: Electronic Control Unit

EVC: Exhaust Valve Closing

GA: Genetic Algorithm

IVO: Inlet Valve Opening

MAF: Mass Air Flow

MDO: Multi-Disciplinary Optimisation

NBI: Normal Boundary Intersection

PSO: Particulate Swarm Optimisation

PRESS: Prediction Error Sum of Squares

RBF: Radial Basis Function

RMSE: Root Mean Square Error

SDNMEP: Standard Deviation of Net Mean Effective Pressure

VCT: Variable Camshaft Timing

VVT: Variable Valve Timing