Catalyst Heating Modeling, Simulation and Optimization

Rodrigo Peralta Moraes Ruiz
Robert Bosch Ltda

Breno Felippe Coimbra Maia, André Menegon Godoy, Rosalvo Bertolucci Filho, Fabrício Tenório Vicente
Robert Bosch Ltda

André Pelisser, João Vitor Carrilho Soares de Carvalho
ETAS

Rodrigo.ruiz@br.bosch.com, breno.maia2@br.bosch.com , andre.godoy2@br.bosch.com , Rosalvo.bertolucci@br.bosch.com , fabricio.vicente@br.bosch.com , andre.pelisser@etas.com , joao.carvalho3@etas.com

ABSTRACT

The product development engineering for emission control has become competitive and complex, mainly due to the continuous evolution of the legislation. The catalyst heating techniques domain is crucial for vehicle emission control. However, understanding which heating strategy promotes the lowest level of emissions is complex in proportion to the number of variables to be explored, making the search for the optimal point a real challenge for automakers and systemists. This work aims to develop a model-based catalyst heating methodology, which helps in the discovery and understanding of possible optimal operating points not explored yet regarding the compromise between emission levels and engine idle speed vibrations. A Machine Learning model was developed and validated based on real catalyst heating data, produced by an automatic starting system that interacts with the engine calibration parameters via Design of Experiment (DoE). The simulation results enabled optimizations through an efficient and analytical method. This method allows a quality delivery of results in a short period of time and enables the search for new horizons on catalyst heating strategies.

INTRODUCTION

Engine calibration is composed of several engineering steps, which must converge and contribute to the approval of a vehicle in terms of emissions [1]. Like any interesting engineering challenge, these calibration steps deal with solutions which are concurrent each other, making the search for the balance point a journey full of obstacles.

One of the most important factors in controlling emissions is the catalyst heating strategy. Catalyst heating is essential for the after-treatment system reach as fast as possible the temperature of high conversion efficiency to reduce tailpipe emissions in a vehicle. However, some control variables of this strategy, establish competition between emission levels, idling quality and driver comfort. In this way, finding the parameterization that establishes the best compromise between these magnitudes becomes complex due the various factors that permeate the day-to-day of calibration engineering, such as: System complexity, project time and cost of tests.

The combination generated by this scenario brings to light the demand for more analytical and automated methods of data analysis, in order to help calibration engineering to find optimized solutions in reduced time intervals, keeping reliability. This type of approach, based on advanced data analysis to find calibration solutions, is called “Model Based Calibration”.

This work aims to develop and explore the “Model Based Calibration” methodology using catalyst heating calibration as an application scenario. The methodology allows an approach through a simulation tool based on data acquired in a vehicle. Data-based simulation opens horizons of prediction and analysis through a virtual interaction between control parameters and the engine. This allows obtaining results in a reduced time interval, in addition to a better understanding between the dependencies of some phenomena that are involved in catalyst heating.

METHODOLOGY

The present study was applied to a 1.6 Liter Port Fuel Injection engine, fueled with ethanol and with variable intake camshaft control. The methodology is based on an automatic calibration system, which can interact with the vehicle through servomotors [1]. Through the DoE (Design of Experiment) methodology, the boundary conditions to be explored are established and the tests performed. From the data obtained, an automated post-processing system is tasked with obtaining specific information about the variables of interest and feeding a Machine Learning model with these

variables. The Machine Learning model, in turn, has the function of providing a broader view of the system, and enables interaction and understanding of phenomena, via simulation. The main purpose is, through the model, to understand the relationship between the control variables, with some outputs of interest. The outputs are: Catalyst temperature, pre-catalyst hydrocarbon emissions, post-catalyst hydrocarbon emissions, idling vibration and fuel debit potential. An algorithm based on Fourier transform was developed to extract, from the engine speed signal, the magnitude of vibration at idle speed.

AUTOMATION SYSTEM - The automation system used in this work was developed in [1].

The system consists of emulating the behavior of a driver by actuating the brake and clutch pedals, as well as the ignition key. For this, servomotors were used and commanded via ETAS ES930, which is programmed using a script developed in INCA FLOW. Figure 1 shows the schematic.

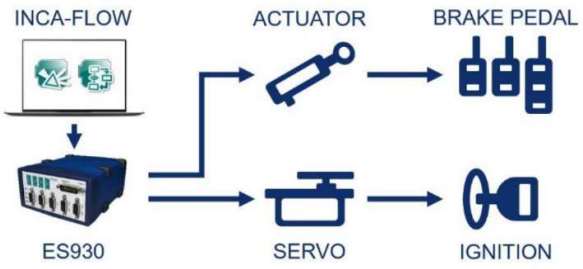

Figure 1. Automation System Diagram.

Source: [1].

The system is capable to measure hydrocarbons emissions level, integrated with the automation system. It is possible through the hardware HFR500, which is a Flame Ionization Detector (FID). It is used to measure hydrocarbon (HC) concentration in a sample gas with a fast response time [2]. The following figure describes the HFR500 diagram.

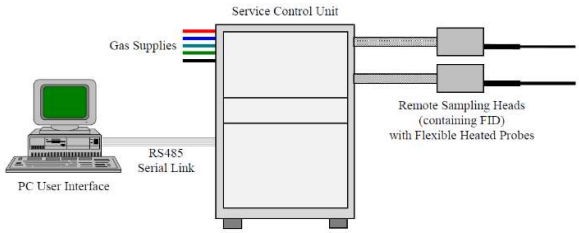

Figure 2. HFR500 Diagram.

Source: [2].

For the integration of this HFR500 hardware with the automation, it was necessary to acquire the AK protocol to open the software interface and develop a code in Python to execute the FID and perform the HC measurement.

Figure 3. User Interface (Protocol AK).

Source: [2].

The exhaust after-treatment instrumentation used in this study is composed by a lambda probe, HC pre catalyst measurement, Catalyst Thermocouple and HC post catalyst. The figure 4 illustrates the instrumentation.

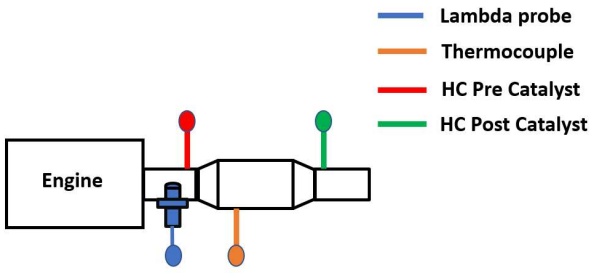

Figure *4*. After-treatment instrumentation.

Source: The Authors.

DoE PLANNING And EXECUTION – Design of experiment is a method to establish boundaries to get model from systems based on its data [3]. The tool used to design and stablish the boundaries in this study was ASCMO Static Planning as well as the tool used to model the system behavior was ASCMO Static Modeling. The complete workflow is described in ETAS ASCMO User guide, as showed in Figure 5.

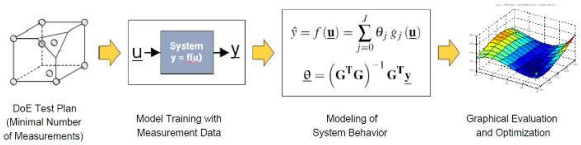

Figure 5. DoE Workflow.

Source: [3].

In this study, ASCMO Static Planning was used to generate the DoE matrix. The methodology to design the experiment in this tool, is based on Gaussian processes. It allows to explore several numbers of relationships of complex phenomena with relatively low effort of measuring to reach high model accuracy [3].

The method used to spread the points to be explored around the sample space in order to balance good model accuracy with low effort of measurement, is called "Space Filling Method". The Table 1 was obtained from ASCMO User Guide and shows the comparison between the Space Filling Method" against the conventional one, in terms of measurement amount.

Table 1. Classic grid measurement versus Space filling method effort.

Source : [3]

Number of Parameters	Number of required Measurements	
	Grid Measurement (5 Steps per Parameter)	DoE Method (Space filling)
4	625	35
5	3125	50
6	15625	70
7	78125	90
8	390625	115
9	1953125	145
10	9765625	175

In this study, de DoE was performed varying 4 control variables, which are:

- Idle Speed Target: **1200 RPM ~1800 RPM**
- End of injection angle: **50° ~ 250°**
- Intake Valve opening angle: **12° Before Top Dead Center (BTDC) ~ 15° After Top Dead Center (ATDC)**
- Spark efficiency: **40% ~ 100%**

To cover all the variable range, 70 measurements were performed.

To execute the DoE, INCA FLOW was used.
the following steps were developed:

- Load DoE block.
- Monitoring oil temperature and half Catalyst temperature to reach 25.5°C and 250°C, respectively.
- Set calibration variables according to DoE.
- Start recording.
- Start engine through robot interface (actuator and servomotor).
- Wait until engine reach 70°C (in idle condition).
- Stop engine.
- Stop recording.
- Wait the Soak time with the fan controlled until the oil temperature returns to 25.5, then rerun the previous process with the next DoE line. So successively until the last line of the DoE.

The Figure 6 shows the INCA FLOW Script.

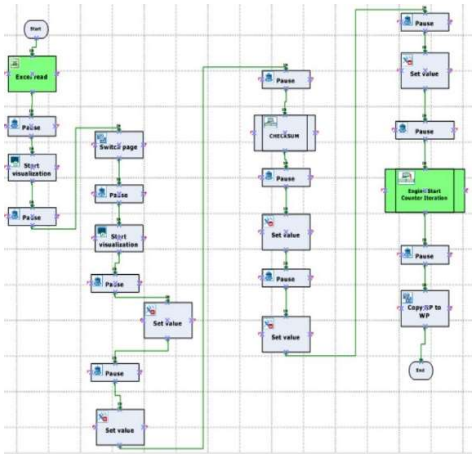

Figure 6. Developed flowchart.

Source: The Authors.

The green Engine Start Counter Iteration block illustrates the set of decision scripts while the other blocks are actions defined by the automation process. The automated system can measure a variety of DoE scenarios.

DATA POST PROCESSING – The data post processing is a script tool based on Matlab® 2020b. Its main function is to find information in the measurements and concatenate this in a structured table. This table will be used later to be both training and validation data in the ASCMO machine learning model.

The information which will be showed in the table, are both related to the input variables which were defined in the DoE, as well as the output variables, that can be generated internally in the post processing tool. Between the main outputs to be observed, are:

- Maximum Catalyst temperature: Maximum value reached in the measurement

- Hydrocarbon concentration: Integrated value during warm up
- Relative Fuel debit potential: Potential to remove start and after-start fuel mass compared with baseline calibration
- Idle Vibration Magnitude

There are many other outputs that can be generated by the post processing script. In general, the post processing workflow is described according with the figure 7.

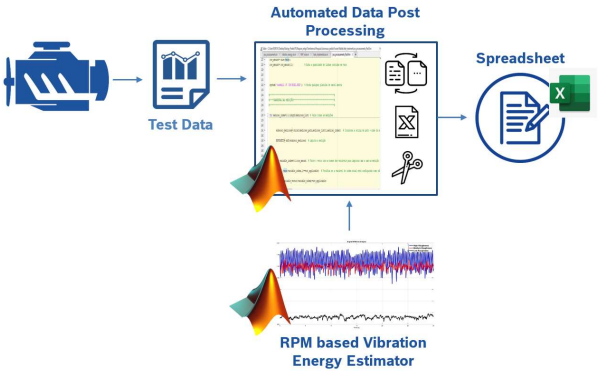

Figure *7.* Post processing Workflow.

Source: The authors.

Maximum Catalyst temperature– The maximum catalyst temperature is obtained by the maximum value reached during the measurement, as illustrated in the figure 8.

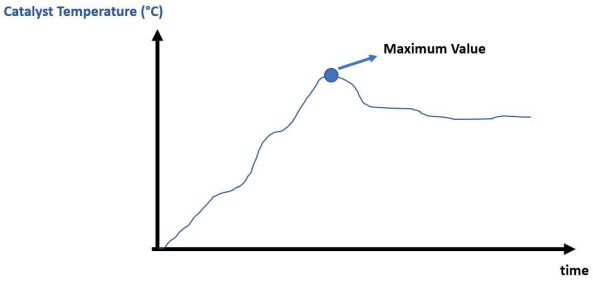

Figure *8.* Maximum Catalyst temperature.

Source: The authors.

Hydrocarbon Concentration–The hydrocarbon concentration both in pre catalyst and post catalyst, is obtained integrating the value read from FID. The final integrated value is the area under the HC curve, as illustrated in the figure 9.

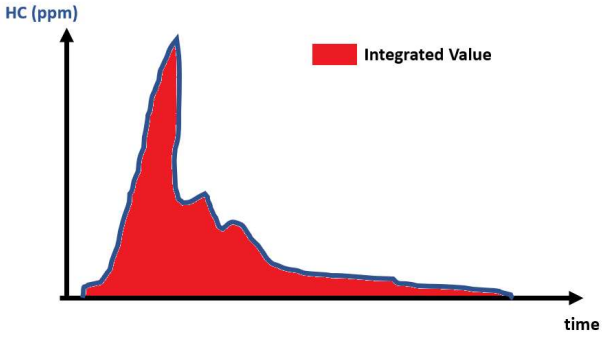

Figure *9.* Integrated HC Concentration.

Source: The authors.

Relative Fuel debit potential– When optimizing catalyst heating, several combustion phenomena are involved. Different combinations of calibration parameters can generate different effects in combustion chamber during the flame propagation, mixture formation and gases exchanges, hence, it will affect the exhaust emissions and catalyst temperature. One of the proposals in executing the DoE methodology, is to sweep the control variables in regions which make sense from the calibration perspective in order to get a wide overview of engine behavior in these regions. When an optimum dataset, which reduces the post catalyst emissions, is found, it is interesting to understand its effect in the combustion phenomenon, looking through a variable that can describe how much the fuel mass is being seized in the combustion. In this way, this variable will give the information if there is or not, potential to remove fuel mass, even after an optimization. It increases the optimization benefits and gives a deeper vision of the optimization effects in combustion.

If an optimized calibration dataset, from catalyst heating perspective, generated a phenomenon in combustion which seizes better the fuel mass, the availability of oxygen concentration in the exhaust will be lower, and the lambda signal will be affected. It indicates that there is a potential to remove fuel mass.

The figure 10 illustrates a situation that a Catalyst heating optimized calibration dataset, generated a better seizing of fuel mass during the combustion, compared with a baseline calibration.

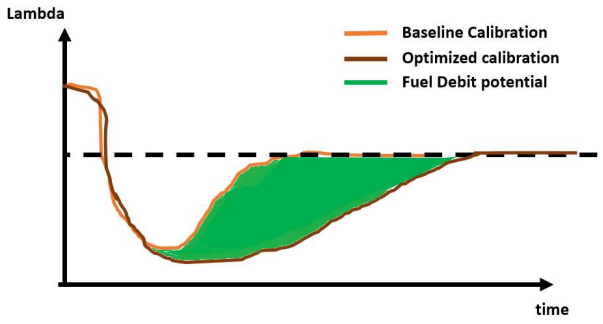

Figure *10.* Positive fuel debit potential.

Source: The authors.

Regardless the dataset which generated this behavior in lambda signal, the difference between the baseline calibration lambda signal (orange curve) and the optimized calibration lambda signal (brown curve), shows the potential that the optimized calibration contains to improve mixture, by reducing fuel mass. This is called in this study as *"Fuel Debit Potential"*, represented in the figure by the green area.

By the other hands, an optimized dataset, from catalyst heating perspective, can generate a worst fuel mass seizing during the combustion, producing higher oxygen concentration in the exhaust, and the lambda signal will be affected as well. The figure 11 illustrates this situation.

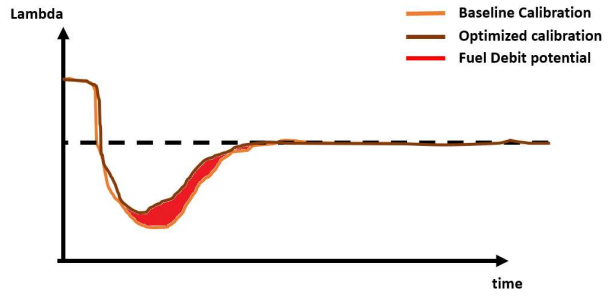

Figure *11.* Negative fuel debit potential.

Source: The authors.

In this case, the optimized calibration from catalyst heating perspective (brown curve) , does not show potential to remove fuel mass when compared with baseline calibration (orange curve). This is called in this study as a negative Fuel debit potential, represented in the figure by the red area.

Therefore, the variable "*Relative Fuel Debit Potential*" can be constructed. And it uses the measurement produced by the baseline calibration. When the dataset produced a lower oxygen concentration in the exhaust, the variable value is positive, showing that there is the possibility to remove fuel mass when compared with baseline. When the dataset produced a higher oxygen concentration in the exhaust, the variable value is negative, showing that there is no possibility to remove fuel mass when compared with baseline calibration.

Vibration Modeling – The engine vibration in idle condition is a very relevant output to be considered when optimizing catalyst heating. The main idea in catalyst heating is to provide thermal energy to the exhaust manifold and it can generate, as a side effect, high levels of vibration in the engine. The tradeoff between the catalyst heating efficiency (which is very correlated with the thermal energy availability in exhaust manifold) and the engine vibration magnitude, is the key to find an emissions calibration solution that can balance emissions level and driver comfort. Besides that, vibration is a "Noise, Vibration and Harshness" (NVH) constraint and, as well as emissions, it needs to be measured, controlled, and minimized.

To obtain a variable which can describe the engine vibration's level, a model was developed to estimate, based on engine RPM signal, the vibration magnitude. The Matlab script, which contains the model, is based on *Discrete Fourier Transform* (DFT).

DFT is applied when there is interest in analyzing discrete signals in frequency domain [4]. A discrete signal is a signal which is composed by samples. The following figure shows a discrete signal composed by "N" samples.

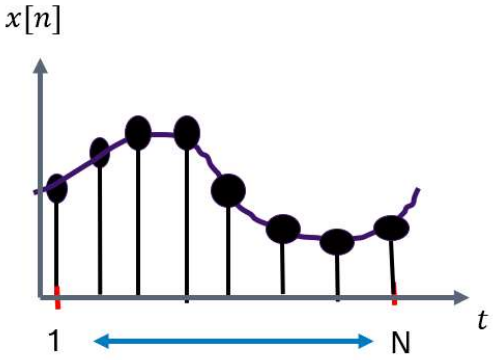

Figure *12.* Discrete signal.

Source: The authors.

The Fourier series exponential representation of a discrete signal, can be described following the equation below [4] :

$$x[n] = \sum_{k=\langle N \rangle} a_k e^{jk\omega_0 n} \qquad (1)$$

Where a_k is a complex phasor which weights the periodic component in the specific frequency. The frequency will be always a multiple of the natural frequency, ω_0.

To build the frequency spectrum signal representation, it is needed to find each a_k component and match it with its respective frequency. The following equation describes how to obtain the components.

$$a_k = \frac{1}{N} \sum_{n=\langle N \rangle} x[n] e^{-jk\omega_0 n} \qquad (2)$$

This methodology can be applied in engine rpm signal in order to obtain the magnitude of the periodic components which composes the signal. This value will be a direct information about vibration. Three different engine vibration levels were used to develop the vibration level model. The figure below, shows these three signals.

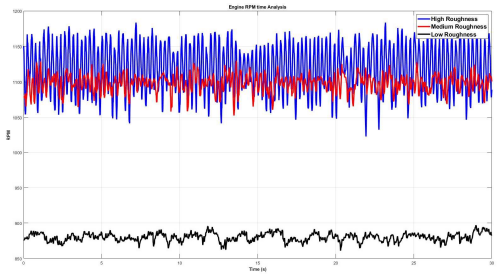

Figure *13.* Engine Roughness in time domain.

Source: The authors.

Using DFT, it is possible to estimate the coefficients a_k , and correlate them with their respective frequencies to build the spectrum visualization. The coefficients a_k represent the amplitude module of each periodic component which describes the signal. The following figure shows the spectrum visualization of the three engine RPM signals showed before.

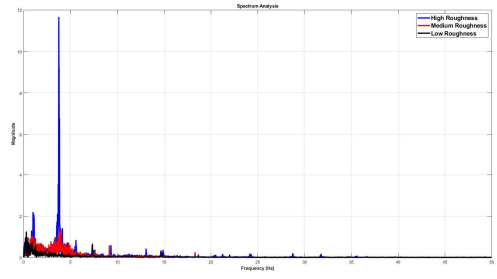

Figure *14.* Engine Roughness in frequency domain.

Source: The Authors.

In frequency domain, it is possible to understand that the roughness in engine speed signals is reflected in the spectrum through higher magnitude component modules a_k , at low frequencies. In this way, the following equation was used to correlate the engine speed roughness with a scalar variable:

$$\boldsymbol{Vibration\ Magnitude} \cong \int_{1}^{N} |\boldsymbol{a_k}| \boldsymbol{d\omega} \qquad (3)$$

Where "N" is the amount of magnitude components, and ω is the frequency. This approach allows to transform the spectrum magnitude in a single variable which can represent all engine speed roughness level in idle. The following figure shows the spectrum and the level associated. The level is extracted from the last value of integral curve indicated the following figure.

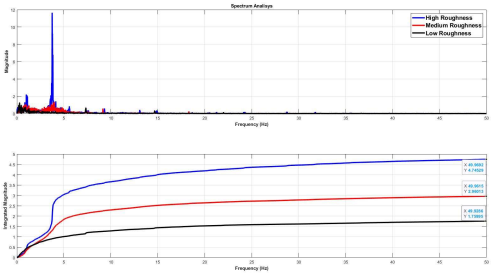

Figure 15. Integrated value of spectrum magnitude.

Source: The authors.

MACHINE LEARNING MODEL USING ASCMO

ETAS ASCMO modelling software was chosen as the platform for generating the catalyst heating behavior estimation. This software relies on supervised machine learning algorithms to generate statistical models based on the Bayesian modelling method.

The Bayesian method consists on defining a prior distribution based on the expected system behavior, and then combining this prior distribution with sampled real data, resulting in a posterior distribution. This posterior distribution can be interpreted as a set of functions that, when combined, may define the observed phenomena. Figure 16 shows an example of the Bayesian method for a 2-point dataset. The first panel show the prior distribution, solely based on assumptions and expectations of the phenomena. The second panel shows the posterior distribution - the combination of the prior distribution and the 2-point dataset.

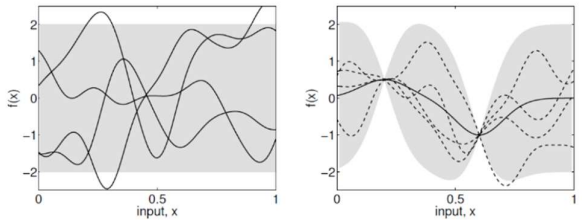

Figure *16*. Example of the Bayesian method application for a 2-point dataset.

On the right panel, the dashed lines represent 4 possible distributions, and the continuous line the mean value of those 4 distributions, which ends up being the model prediction. As an interesting benefit, the Bayesian Method also estimates the models in this case represented by the shaded area, accounting for twice the local standard deviation for each input x.

ASCMO implements the classic approach of the Bayesian Method using a Gaussian Process as the basis for the prior distributions. Since this methodology derives from the Gaussian Probability Distribution, a stochastic process governs the properties of those functions [5]. It is also noted that this approach dispenses parametric models and instead, defines a prior probability distribution over functions directly [6].

Detailed mathematical expansions on both the Bayesian Method and the Gaussian Regression Process can be found at various sources, such as Rasmussen X, Bishop Y and Pelisser et al Z.

As a result of those given statistical and data-based approaches, the modelling method applied by ASCMO suits perfectly the needs for this study regarding the expected high complexity of the correlations, model self-validation and good model quality even when big datatsets are not available.

In this study, after the data post processing, a post processed matrix is available to feed the ASCMO on order to estimate the virtual model of engine behavior. The following figure illustrates this process.

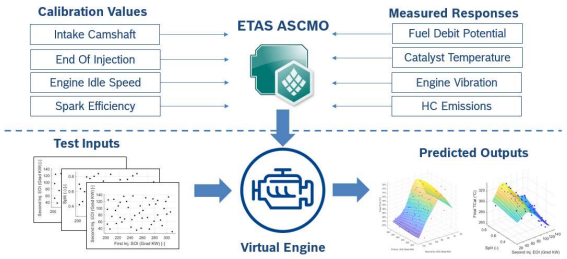

Figure *17*. ASCMO modeling workflow.

Source: The Authors.

RESULTS AND DISCUSSIONS

MODEL SIMULATION – In ASCMO the model is represented in a 2D screen which contains all the dependencies profiles between the inputs explored in the DoE and the outputs of interest. In the horizontal axis are the inputs and in the vertical axis, the outputs. The figure 18 shows the model.

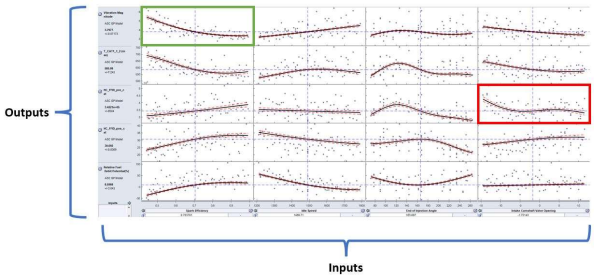

Figure *18*. ASCMO Model representation.

Source: The Authors.

For each input and output, there is a distribution curve based on the measured data, which represent the dependency between the couple of input and output, it is, how each specific input affects each output. For example, the green square marked on the figure 18, represents the dependency profile of the relationship between Vibration Magnitude and Spark Efficiency. The red square, marked on the figure 18, represents the dependency profile of the relationship between the Intake Camshaft Valve Opening Angle and the HC concentration pre catalyst. This logic is valid for all the distribution curves plotted on the screen.

In the simulation tool, the Leave-One-Out method is used to make a pre analysis of the prediction quality. The method consists in estimating n models, each with n-1 training data. Afterwards, the precision is determined based on the point which is not involved in the model estimation [3].

The model quality is quantified by the Root Mean Square Error (RMSE) and the R^2.

The RMSE is defined as the following equation [3].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{i_{pred}} - X_{i_{meas}})^2}{n}} \qquad (4)$$

Where n is the number of measured points. $X_{i_{pred}}$ is the predicted value and $X_{i_{meas}}$ is the measured value.

The R^2 is obtained from the comparison between the variance that remains after the model training and the variance concerning the mean value of all measuring data [3].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{i_{pred}} - X_{i_{meas}})^2}{\sum_{i=1}^{n}(X_{i_{pred}} - \bar{X}_{meas})^2} \quad (5)$$

The figure 19 shows the RMSE and R^2 for each output.

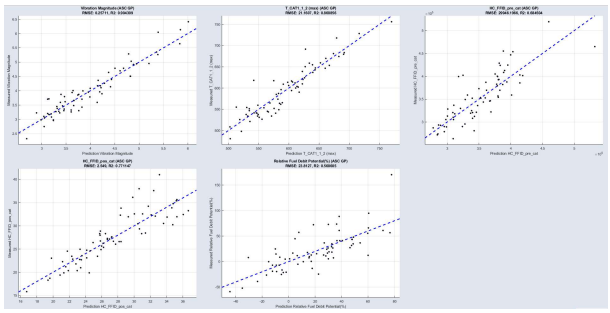

Figure *19.* R^2 and RMSE of each output prediction.

Source: The Authors.

The Vibration Magnitude, Catalyst Temperature and HC Concentration Post Catalyst, showed higher precision in prediction using Leave-One-Out method when compared with HC pre catalyst and Relative Fuel Debit Potential. One possible reason for this is due these variables are very connected directly with the combustion residues, hence, very susceptible to combustion variations. In this study, a validation will be presented later to understand the reasons why there is difference in the prediction quality between the outputs.

VIBRATION MODEL VALIDATION – To validate the vibration model based in the Engine RPM signal, a three-axes accelerometer signal was used to be compared with the RPM Vibration Magnitude estimation via ASCMO model.

The accelerometer is located under the handbrake to get the vibration information in the vehicle interior.

The x-axis is measuring vibrations in longitudinal direction. The y-axis is measuring in transversal direction, the z-axis is measuring in the normal direction. The figure 20 illustrates the accelerometer axes configuration in vehicle.

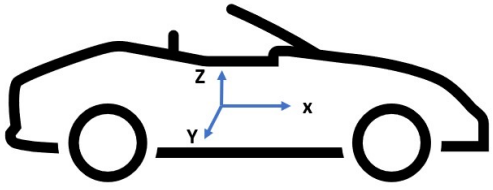

Figure 20. Accelerometer Axes.

Source: The authors.

To obtain the vibration absorbed by the accelerometer, a specific signal processing method was used, which is the Spectrum Energy Estimation, the method is the spectrum Root Mean Square (RMS). To get the RMS value in a spectrum representation, the root sum square of all spectral magnitude components ($\boldsymbol{a_k}$) is calculated [5]. The following equation describes the RMS value of a spectrum

$$RMS = \sqrt{\frac{a_0^2}{2} + \sum_{i=1}^{k-1} a_i^2 + \frac{a_k^2}{2}} \quad (6)$$

The a_k term is the same presented before. RMS is a single number which represents the level of spectrum energy [7]. The figure 21 shows the relationship between each axis of accelerometer signal (vertical axis) and the RPM vibration magnitude estimator (horizontal axis).

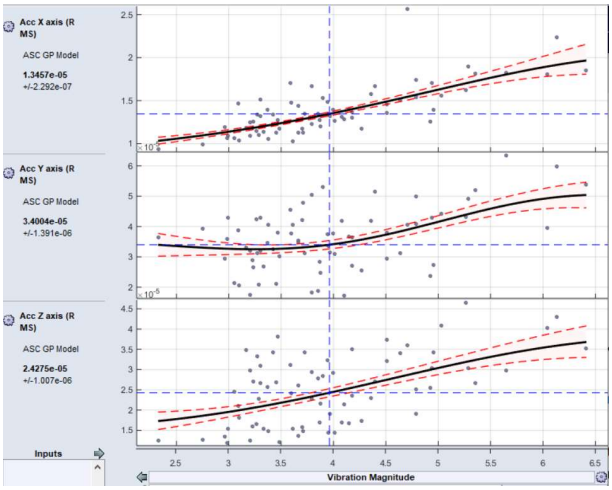

Figure *21.* Accelerometer axes versus RPM Vibration Magnitude Estimator.

Source: The Authors.

The figure 21 demonstrates clearly that Vibration Magnitude Estimator has a directly proportional relationship with the vibration absorbed by the accelerometer in all axes. For this reason, in this study, the RPM Vibration Magnitude Estimator was used as reference to measure and qualify the Engine RPM vibration level, once it is a information present in any Engine Control Unit and turns the methodology more flexible.

GAUSSIAN MODEL VALIDATION – To validate the Gaussian model, three different tests were performed in three different model regions. The first boundary condition is according to the following figure:

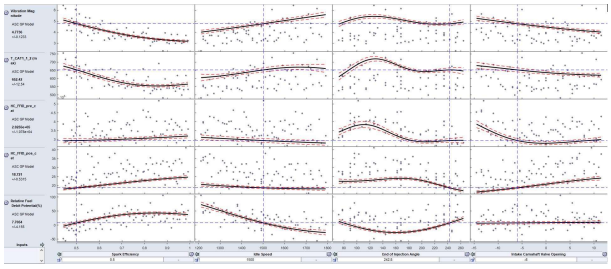

Figure *22.* Test 1: Boundary Condition.

Source: The Authors.

The boundary condition in the first test (Test) is :

- Idle Speed Target: **1500 RPM**
- End of injection angle: **242,9 (°)**
- Intake Valve opening angle: **6° BTDC**
- Spark efficiency: **50%**

The second boundary condition (Test 2) is showed in the figure 23.

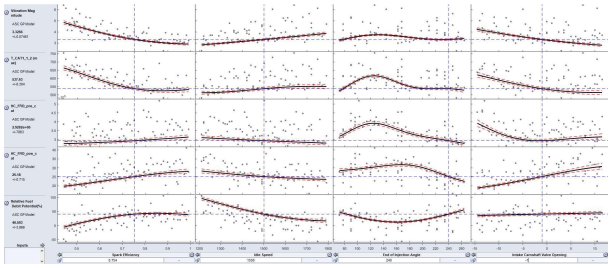

Figure *23.* Test 2: Boundary Condition.

Source: The Authors.

The boundary condition in the second test is:

- Idle Speed Target: **1500 RPM**
- End of injection angle: **240 (°)**
- Intake Valve opening angle: **1° BTDC**
- Spark efficiency: **75%**

The third boundary condition (Test 3) is showed in the following figure.

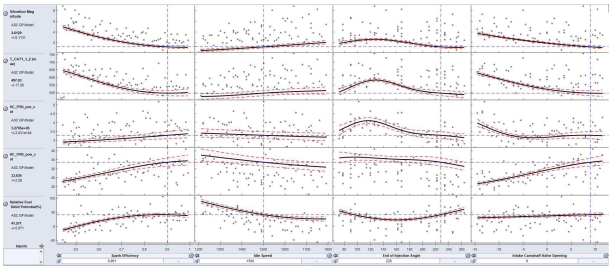

Figure *24.* Test 3: Boundary Condition.

Source: The Authors.

The boundary condition in the third test is:

- Idle Speed Target: **1500 RPM**
- End of injection angle: **228 (°)**
- Intake Valve opening angle: **9° ATDC**
- Spark efficiency: **90%**

These three conditions were reproduced in vehicle to compare the in-vehicle results with the model prediction. For each condition, 5 measurements were performed, totalizing 15 measurements. The purpose is to cover repeatability between measurement, once that all the phenomena which are being analyzed are related with combustion, a stochastic phenomenon.

The table 2 shows the results of the first test.

Table 2. Test 1 Results.

Source : The authors

Test 1					
Vibration Magnitude		Temp Cat	HC pos Cat	HC pre Cat	Relative Fuel Debit Potential(%)
Model	4,73	649,24	18,80	297900,00	13,25
Mean	4,03	631,79	21,74	283134,35	5,74
Error	0,70	17,45	2,94	14765,65	7,51
Error(%)	17,37	2,76	13,54	5,22	130,79
Std	0,05	2,21	2,02	13298,33	4,88

The class **"Model"** is the ASCMO model prediction. **"Mean"**, is the mean result of each variable between the 5 measurement which were performed in that test. **"Error"** is de absolute difference between the model and the mean. **"Error (%)"** is how much percent the model is distant from the mean, and **"Std"** is the standard deviation of each variable between the 5 measurements which were performed in that test.

The table 3 shows the results of the second test.

Table 3. Test 2 Results.

Source : The authors

Test 2					
	Vibration Magnitude	Temp Cat	HC pos Cat	HC pre Cat	Relative Fuel Debit Potential(%)
Model	3,33	538,09	25,13	293690,00	39,93
Mean	2,64	525,41	26,04	322308,13	36,07
Error	0,69	12,68	0,92	28618,13	3,86
Error(%)	26,10	2,41	3,52	8,88	10,70
Std	0,04	4,56	0,73	10484,64	4,48

The table 4 shows the results of the third test.

Table 4. Test 3 Results.

Source : The authors

Test 3					
	Vibration Magnitude	Temp Cat	HC pos Cat	HC pre Cat	Relative Fuel Debit Potential(%)
Model	2,61	496,33	33,60	328840,00	40,34
Mean	2,41	522,17	28,67	320765,87	38,05
Error	0,20	25,84	4,93	8074,13	2,29
Error(%)	8,10	4,95	17,21	2,52	6,02
Std	0,02	1,13	0,63	4879,67	3,82

The purpose of the tests is to sweep the model in three significantly different regions to explore the prediction capacity and the results robustness. With this kind of analysis, it is possible to understand if the amount of data is being enough to provide, or not, a good confidence interval in all regions.

The prediction robustness can be classified in 2 classes according with the capacity to minimize the error between the model and the real engine behavior. The first one is the qualitative prediction capacity, which is related to the model capacity in always hit the result trend, but not the absolute value. The second, is the quantitative prediction capacity, which is related to the model capacity in hit the result values with a high accuracy.

In the first test, the prediction robustness of Catalyst temperature and HC post catalyst, were excellent, and it fits in a quantitative prediction class. The prediction robustness of Vibration Magnitude was good, and it still has some level of confidence to be considered a quantitative prediction, but not with the same quality of HC post catalyst and Catalyst Temperature. The prediction of Relative Fuel Debit Potential does not show robustness to be a quantitative prediction class in this specific test, but it can still be considered as a qualitative prediction, once the model predicted that there was potential to remove fuel (positive Fuel Debit Potential) and it fits with the reality.

In the second test, the prediction of Catalyst Temperature, HC post catalyst, Relative Fuel Debit potential were excellent and can be classified as a quantitative prediction. The Vibration Magnitude prediction was good and can be understood as well as a quantitative prediction.

In the third test all the predictions value are very well fitted with the real engine behavior, and all can be considered as a high quality of quantitative prediction.

When it comes about combustion, quantitative capacity is something very sensible. Combustion is a stochastic phenomenon, it means, the result is influenced by a lot of random and unpredictable combinations of inputs. Some environmental conditions, increase this randomness, for example, the temperature. The colder the engine coolant temperature, or the intake air temperature, more unpredictable the combustion result. If considered that the present model is proposed to predict from the cold phase, until the warmed-up engine (the whole warm up phase), a lot of randomness is involved. For this reason, a good qualitative prediction is acceptable in this model application.

The HC pre catalyst concentration is being validated, but it will not be considered in the model optimization. The purpose to have HC pre catalyst in the analysis is to understand the effects in combustion phenomena before the effect of catalyst conversion. But the main focus in optimization will be the HC post catalyst.

In the first test, the Relative Fuel Debit Potential did not fit in a quantitative quality. The reason is due the test condition, especially regarding the Spark Efficiency value (50%). It promotes instability in the combustion, turning harder the repeatability of the test and increasing the standard deviation between the measurements. As the Fuel Debit Potential is based in the lambda signal, which depends on the oxygen concentration in the exhaust manifold, it repeatability is directly related with the combustion residues, hence, if the combustion is unstable the Fuel Debit Potential will be as well.

Based on the validation results analysis and the previous considerations related to the combustion phenomenon, the model demonstrated high capacity in prediction robustness in all regions for all variables of interest.

OPTIMIZATION POTENTIAL – Once the model prediction is reliable, the optimization through simulation is possible and reliable as well.

ASCMO has different optimization options. In the single criteria optimization, a variable is optimized according to the gradient descent method. When it comes about gradient, it is related with functions which contains multiples inputs and a single output.

In the first optimization simulation, the single criteria was used to minimize HC post catalyst, establishing a maximum value to engine speed idle target in 1400 RPM.

Compared with the baseline calibration, the optimization simulation reduced nearly in 50% the HC post catalyst concentration, but it increased nearly 24% the vibration magnitude. The fuel debit potential after the first optimization simulation is estimated nearly in 34% compared with the baseline calibration.

To explore the tool potential in emission reducing, keeping the vibration magnitude a second optimization simulation was carried out. A a hard upper bound was established in vibration magnitude in the same value of baseline calibration. In the second optimization with vibration magnitude hard upper bound, the HC post catalyst

concentration was reduced nearly in 42% compared with the baseline calibration. The vibration magnitude is the same of baseline and the fuel debit potential is 81% compared with the baseline.

Although the HC post catalyst has a higher value in the second optimization compared with the first one, the fuel debit potential increased significantly, and the vibration magnitude was kept if compared with the baseline. With a fuel debit potential in this in a higher value, the fuel mass could be reduced in the calibration and the final proposal could be even more optimized than in the first optimization attempt. It can indicate that, in the optimization criteria, it is needed to pay attention not only in the HC post catalyst but in fuel debit potential as well.

A third optimization simulation was performed. The criteria was, minimize HC post catalyst, keep de vibration magnitude in a hard upper bound with the same value of the baseline calibration and maximize fuel debit potential. In the third optimization, HC post catalyst was reduced in 31% compared with baseline calibration. Vibration energy was reduced in 18% and the fuel debit potential increased to 162%. Besides that, in this optimization the engine speed idle target was calculated in 850 RPM, which could bring an effect in fuel consumption as well.

It is important to find the tradeoff between maximizing fuel debit potential and reducing HC post catalyst to understand the how it affects the final emissions values in emission cycles. In this study, these optimizations were not validated in emission cycle, and it will be considered in future studies.

CONCLUSION

The method of Model Based Calibration allows the optimization of complex systems by comparing the model predictions and real measurements in a very large operation range. The most significative consequence is the gain of efficiency directly related to costs reduction (reduction of resources demand and development time). A previous estimative shows a reduction about 60% in costs and 25% in time for a catalyst heating workpackage calibration for a medium complexity system (PFI, monofuel and one side VVT). There is also a quantitative non-mensurable gain for know-how by the possibility of visual observation of innumerous variables correlation in a very large spectrum via systematic way.

With those considerations, it is clear the powerful competitive advantage of the described method. It allows the development of data products with high excellency, most efficient and cost-effective.

The initial results open a promising window for application of the method for higher complex systems with different engine configurations. This method flexibility characteristic is one of the points of interest from this working group and some future activities are already planned as next steps.

It is also an important point of interest the consolidation of this work as a different method (with potentially superior quality) compared to the current and traditional calibration tasks for specific workpackages. It opens a real possibility of inclusion of a specific calibration service into the supplier portfolio.

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