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Designing optimal control maps for diesel engines for high efficiency and emission reduction

Hoang Nguyen Khac[1] and Kai Zenger[2]

Abstract— **The objective of this paper is to design static optimal control maps of diesel engines to achieve high efficiency and emission reduction. The calibration tool applied to create the control maps, named "Off-line parameterization tool", was designed based on the Design of Experiments method. The optimization goal is to minimize the Brake Specific Fuel Consumption (BSFC) by the engine's input parameters under emission constraints. The tool was designed to work both fully automatically and semi-automatically. Many reports on engine calibration have taken the Design of Experiments (DoE) approach, but their implementations in choosing experimental design types and optimization processes are different compared to this paper. The unique aspect of this research lies in the significant properties of the Off-line parameterization tool. First, this tool is flexible: it is able to work with multiple inputs and multiple outputs. Second, it can reduce the calibration time as the engine running time is kept as short as possible and all the data processing work is accomplished automatically.**

I. INTRODUCTION AND MOTIVATION

Engine calibration constitutes a critical process since the presence of diesel engines in industry. Engine calibration (known as engine tuning) refers to the adjustment or modification of the internal engine's actuators or its control unit in order to yield optimal performance and fuel economy. The need for keeping the engine running at higher efficiency and lower emissions requires calibration work to achieve sophistication and accuracy.

Increasing the number of controllable engine parameters leads to a dramatic increase in calibration costs. Hence, the new generation of engine calibration must be capable of handling a high number of parameters with reasonable costs. Static control maps (look-up tables), in which the optimal values of the engine's actuators are contained, have been a common control strategy in the automotive industry. Finding the accurate values for these maps is therefore really challenging for the manufacturers. Several works have been carried out to solve this problem. A D-Optimization and DoE based method has been demonstrated in [1], however, the method can only deal with single-object optimization problem (air mass flow as an example in this article). More versatile and sophisticated approach has been presented in [2], the proposed method used combinations of complex models to deal with multi-objective functions. Promising results were shown in this work but its computational complexity is too high.

The objective of this paper is to introduce a calibration tool to create static optimal control maps of diesel engines for high efficiency and emission reduction. This tool, namely "Off-line parameterization tool", was designed based on the Design of Experiments method with the computation works kept to fairly small. The optimization goal is to minimize the Brake Specific Fuel Consumption (BSFC) of the engine by adjusting the engine's input parameters under emission constraints.

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II. RESEARCH AND METHODOLOGY

This section presents a short discussion on effects of some selected input parameters on the engine's performance. Moreover, the Design of Experiments method and the off-line parameterization tool are introduced.

A. Effects of the input parameters on engine's performance

In this paper, the following input parameters are considered: the intake pressure P_i, the common rail pressure P_{CR} and the start of injection SoI. No pre- or post-injection is included at this stage. Each of the three input variables is expected to have an effect on the BSFC, which represents the fuel flow rate per unit power output. The BSFC is by definition

$$BSFC[g/(kW.h)] = \frac{\dot{m}_f[g/h]}{P[kilowatts]} \tag{1}$$

in which $\dot{m}_f$ is the fuel flow rate in grams per hour and P is the produced work in kW.

1) Effects of intake pressure.: The intake pressure (boost pressure) plays an important role in diesel engine control. It has an enormous impact on how efficiently the engine is performing and, most importantly, how the intake pressure affects the exhaust emissions of the engine.

Compressed air is used to create heat to burn the fuel. A high intake pressure can increase the efficiency of fuel combustion. High efficient combustion reduces unburned components so the exhaust emissions can be reduced [3]. Higher intake pressure increases the concentration of oxygen (O_2) to improve the combustion; however, higher intake pressure simultaneously increases the concentration of carbon dioxide (CO_2) emissions due to the optimal reaction between carbon in the fuel and highly concentrated oxygen.

Moreover, higher air intake pressure increases the NO_x emission. According to Zeldovich's mechanism [4], the NO_x formation increases with high pressure and high temperature of the combustion. However, particle mass emission is in fact decreased significantly with high intake pressure [5].

2) Effects of common rail pressure.: Common rail pressure has intense effects on the engine combustion quality as the injection pressure affects the fuel spray. Raising the rail pressure to an appropriate range can help reduce smoke and increase the fuel economy, but at the same time the NO_x emission is increased [6].

Common rail pressure can have different effects upon different working conditions of the engine. Under heavy load condition, too high a rail pressure does not clearly improve the smoke and fuel economy but the NO_x emission is still increased. On the other hand, too high a rail pressure under light load condition increases the BSFC too much [7]. On low and middle load, a high enough rail pressure can reduce both smoke and NO_x emissions.

3) Effects of injection timing.: The start of injection determines when the fuel is injected into the cylinder and kicks off the combustion. The timing is defined to be before the piston reaches the top dead center. Earlier SoI can result in high in-cylinder pressure, temperature and NO_x emission while later SoI results in a reversed outcome [8]. However, early injection produces higher efficicency and thus reduces the fuel consumption.

According to [9], the use of early SoI provides lower soot and higher NO_x emission compared to the use of later SoI. The later injection is usually deployed to effectively reduce NO_x.

B. The design of experiments method

The control of most modern engines consists of three main loops, including the fuel, air and EGR paths. Co-ordinated control of these three paths is required for minimization of emissions and consumption of fuel. The control strategy typically consists of two essential components: static control maps and feedback/feedforward control. However, the feedback control naturally relies on the set-point, which has to be provided. In the case of CI engines, such set-points are stored in the form of the lookup table (or engine map) and include, for example, manifold and common rail pressure set-points and injection timings. Without having these, a feedback control would be meaningless, as the set-points have to be carefully chosen to provide optimal engine performance. Therefore, calibration of the lookup tables remains one of the most important steps in the engine control system design.

The fuel consumption and the emissions are the two most important factors that need to be minimized in internal combustion engines. While a brute force can be used to guess these parameters, a structured way is preferred to save resources and time. In this work, a design of experiments approach is proposed as a powerful tool to create and analyze statistically models of the process. The look-up tables required for the engine to run include the intake pressure and common rail pressure set-points and start of injection (SoI). Design and optimization of the tables is generally a time consuming trial and error procedure. Fig. 1 demonstrates the calibration of the three maps for one engine operating point (OP). It can clearly be observed that a brute force trial and error method can hardly be used to find the

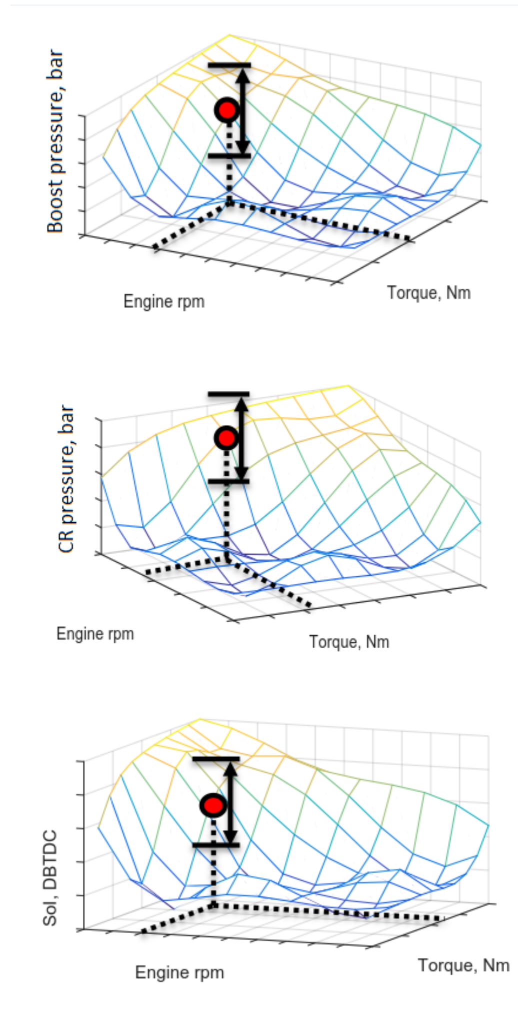


Fig. 1. SIMULTANEOUS CALIBRATION OF THREE PARAMETERS AT SINGLE ENGINE OP.

optimal factors combination and requires many engine runs. While the DoE approach does include experimentation as well, it is an organized and structured approach. Another advantage of DoE is its ability to evaluate the effect of several factors at a time, rather than using a one-factor approach. The combination of the aforementioned input parameters has to be found at each engine operating point so that the BSFC is minimized under some emission constraints such as NO_x emissions.

1) Box-Behnken design.: In this work, the Box-Behnken design is used to determine the relationship between the input parameters and the engine response BSFC. The three chosen input factors are intake pressure (bar), common rail pressure (bar) and start of injection (dBTDC). They are coded as x_1, x_2 and x_3, respectively. The engine response BSFC is coded as y and the i^{th} emission measurement is coded as y_i.

In this design, each of the 3 factors is assigned high (+), low (-) and middle (0) levels which are chosen based on the knowledge of the process. These levels must be chosen taking into account their feasibility and safety at the current engine operating point. The design matrix is shown in Tab. I.

TABLE I
TABLE OF RUN FOR THE BB 3-VARIABLES EXPERIMENT.

BB (3)			
x_1	x_2	x_3	**No. of runs**
±1	±1	0	4
±1	0	±1	4
0	±1	±1	4
0	0	0	3
Total runs			15

=

Std	x_1	x_2	x_3
1	-	-	0
2	-	+	0
3	+	-	0
4	+	+	0
5	-	0	-
6	-	0	+
7	+	0	-
8	+	0	+
9	0	-	-
10	0	-	+
11	0	+	-
12	0	+	+
13	0	0	0
14	0	0	0
15	0	0	0

The Box-Behnken design was chosen based on its number of runs needed as well as its abilities to guarantee good quadratic models [10].

Once the design matrix if formed, the experiments can be run on the engine testbed and the measurements are recorded. The regression model with three independent variables (P_i, P_{CR} and SoI) and the one response (BSFC) is fitted

$$\begin{aligned} BSFC = a_0 + a_1 P_\mathrm{i} + a_2 P_\mathrm{CR} + a_3 SoI + \quad &\text{(linear terms)} \\ a_{12} P_\mathrm{i} P_\mathrm{CR} + a_{13} P_\mathrm{i} SoI + a_{23} P_\mathrm{CR} SoI + \quad &\text{(interaction terms)} \\ a_{11} P_\mathrm{i}^2 + a_{22} P_\mathrm{CR}^2 + a_{33} SoI^2 \quad &\text{(quadratic terms)} \end{aligned} \tag{2}$$

where the coefficients a_i are estimated using the least squares regression method. The model has all three linear terms of the inputs plus interaction terms between each two of them and finally quadratic terms of each of them. The quadratic terms also ensure curvature in the response.

A similar regression model is used to present the correlation between the three input factors and the emission measurement, particularly NO_x at this stage.

$$\begin{aligned} NO_x = b_0 + b_1 P_\mathrm{i} + b_2 P_\mathrm{CR} + b_3 SoI + \quad &\text{(linear terms)} \\ b_{12} P_\mathrm{i} P_\mathrm{CR} + b_{13} P_\mathrm{i} SoI + b_{23} P_\mathrm{CR} SoI + \quad &\text{(interaction terms)} \\ b_{11} P_\mathrm{i}^2 + b_{22} P_\mathrm{CR}^2 + b_{33} SoI^2 \quad &\text{(quadratic terms)} \end{aligned} \tag{3}$$

where the coefficients are also estimated by the least square method and in the later steps, this fitted model will be used as non-linear constraints for the optimization procedure.

2) Optimization process: Once the model of BSFC in terms of the three input factors has been formed, the engine will be optimized such that

$$\begin{aligned} &\underset{P_i, P_{CR}, SoI}{\text{minimize}} && BSFC \\ &\text{subject to:} && emission \quad constraints \end{aligned} \tag{4}$$

in which (2) is used as the cost function while (3) is used as the non-linear constraint in a sense that the estimated NO_x is less than or equal to a number α (which is predefined according to emissions regulations) .

The non-linearly constrained optimization problem is solved by using the Sequential Quadratic Programming (SQP) algorithm. The basic idea of SQP is to iteratively model the non-linear optimization problem at a given number of iteration x^k as a Quadratic Programming subproblem, and to use the solution from the subproblem to build a new iteration (or approximation) x^{k+1} [11].

C. The off-line parameterization tool

The engine calibration process is classically divided into three phases [12]:

1. Preliminary phase: choosing a set of operating points to study and emissions targets.
2. The optimization of engine responses on each OP under emissions targets.
3. The construction of the maps with smoothening step between optimal settings.

Based on this structure, the off-line parameterization tool's working diagram is made with some modifications as

(i) The first step is preparation for the Design of Experiments setup in which the type of experimental design and the optimization variables must be defined. The Box-Behnken design table is chosen due to its simplicity and ability to produce good experimental data. The optimization variables are coded as
   1. Input factors:
   - Boost pressure: x_1. (unit: bar)
   - Common rail pressure: x_2. (unit: bar)
   - Start of injection: x_3. Unit: degree Before Top Dead Center (dBTDC).
   2. Responses:
   - The Break Specific Fuel Consumption (BSFC): y_1 (unit: g/kWh)
   - Other possible emissions responses such as NO_x and NO responses: y_i

   Although there are multiple inputs and multiple outputs, this is not the case of multiple input-multiple output modelling. Each of the output responses is modelled separately based on the inputs.

(ii) The second step is selecting the operating points by which the engine is run. The points are chosen in a 300 round-per-minute interval of speed and about 8-16 load points. The interval between points may differ from the engines and should be carefully considered beforehand. In addition, ranges of the variables should also be predetermined. The complexity of the fitting model for engine's response depends on the size of these ranges. Low order polynomials are usually sufficient to precisely model the response by using a small enough domain. This step is also a starting point of a closed-loop process. This loop is run for each operating point, starting from the first one and finishing at the last one.

(iii) The next two steps require actual engine running. First task involving the engine is the validation of the domains which were predetermined in the previous step. The experimenter runs the engine with predefined

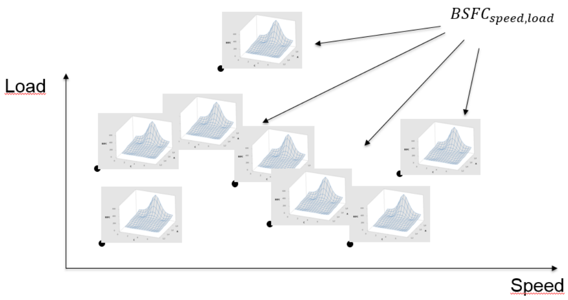


Fig. 2. INITIAL OPTIMAL MAP WITH LOCAL OPTIMA.

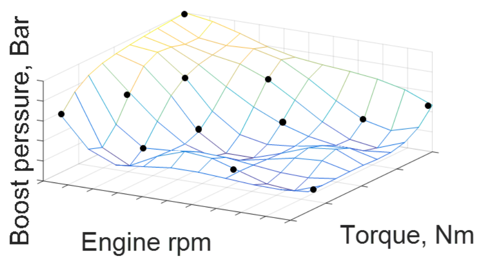


Fig. 3. EXAMPLE OF A MAP ON THE WHOLE OPERATING RANGE.

domains to check whether the upper and lower levels of the input parameters are out of the engine's operating range. As all tests are predefined, the experiments can be run automatically if it is safe to let the engine run on itself. Data of inputs and response values are recorded separately for each operating point.

(iv) Modelling and optimization processes can be run right after finishing of all the experiments at each operating point. In case it is not safe to keep the engine running with the tool automatically, experiments of all operating points will be conducted without going to the modelling step. As the data has been recorded separately, modelling and optimization can be done after the test runs. That is why the tool is called "off-line" as the computations can be done without running the engine. The optimizing can be formulated as a classical mathematical problem of optimization under constraints. In this approach, the optimization is performed at one OP after the other, considering the responses of emissions for each OP as constraints.

(v) When optimization is done for all of the operating points, optimal values of each input factor are saved to initial optimal maps similar to the one in Fig. 2. They are just scatter plots of all the optimal settings and the next step is building a final map on the whole engine operating domain based on those values. Several fitting methods can be applied to build the map, such as *Robust Locally Weighted Regression* [13] method. Notice that the selected number of operating points has a big impact on the map's resolution and accuracy. The denser the map is, the more points is needed. Fig. 3 shows an example of a map on the whole engine operating range.

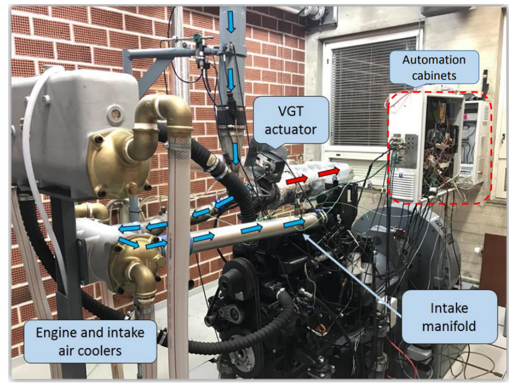


Fig. 4. AGCO POWER 44 AWI.

TABLE II
SELECTION OF OPERATING POINTS.

Speed (rpm) / Injection quantity (mg)	1300	1600	1900	2200
15 mg				
30 mg		✓	✓	✓
45 mg	✓	✓	✓	✓
60 mg		✓	✓	✓
75 mg	✓		✓	

(vi) One more step must be done before the created maps can be used. The final phase of the tool is to smooth the set-point maps. Since the changes of the parameters are not feasible during transient, the maps need to be smoothen to avoid rough transitions between operating points. Hence, the optimal points are often shifted away from their locations during the smoothing process. The goal is to remain as close as possible to the local optima while keeping a smooth shape of the map.

III. EXPERIMENT IMPLEMENTATION

A. Engine testbed

The engine test bed to be used in this work is a four-cylinder, common rail and turbocharged diesel engine in the *Internal Combustion Engine Laboratory* at Aalto University. The engine model is AGCO POWER 44 AWI and is shown in Fig. 4.

Running all the experiments required for one operating point takes around one hour since the engine is very sensitive and it requires careful handling during the operation.

Due to these reasons, this engine test bed is only used for testing of operating points to find out the ranges of factors. The experiments are conducted on a simulation engine model which was calibrated with the AGCO engine. The model was developed in GT-Power software by David Bernasconi [14].

B. Operating point selection

According to the GT-Power model, the operating points are defined based on speed (rpm) and injection quantity (mg). The chosen points are shown in Tab. II

TABLE III
MATRIX RUN DESIGN FOR EACH OPERATING POINT.

P_i	P_{CR}	SoI	**BSFC**	**NOx**
-1	±1	0		
+1	±1	0		
-1	0	±1		
+1	0	±1		
0	-1	±1		
0	+1	±1		
0	0	0		
0	0	0		
0	0	0		

TABLE IV
MODELING RESULTS OF THE SELECTED OPERATING POINTS.

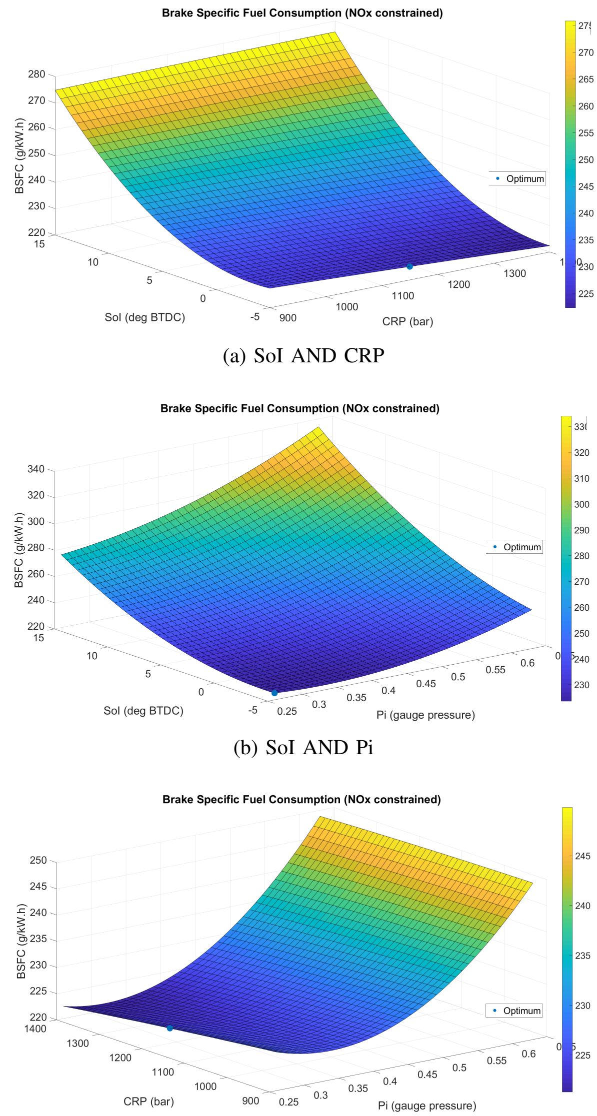
Operating Point	Root Mean Squared Error (BSFC)	R^2	$R^2_{adjusted}$
1	2.32	0.987	0.965
2	1.39	0.995	0.987
3	3.15	0.996	0.99
4	3.36	0.993	0.982
5	2.25	0.995	0.986
6	11.3	0.986	0.961
7	7.09	0.991	0.975
8	6.04	0.989	0.97
9	4.54	0.992	0.979
10	25.5	0.974	0.927
11	12.5	0.985	0.959
12	6.24	0.994	0.983

C. Matrix run preparation

The matrix run is designed based on the Box-Behnken design and is shown in the Tab. III. The last two columns are reserved for the measured data to be filled in.

D. Running experiments

All the points with the check mark (✓) in Tab. II were run in the simulation model and the results of BSFC as well as the emissions were recorded for later phases. Modeling and optimization processes were executed after all operating points had been run.



(a) SoI AND CRP

(b) SoI AND Pi

(c) CRP AND Pi

Fig. 5. OPTIMIZATION UNDER EMISSION CONSTRAINTS.

IV. RESULTS AND DISCUSSION

The final outcomes of this work are three look-up tables of the intake pressure P_i, the common rail pressure P_{CR} and the start of injection SoI. These tables contain the optimized values which can minimize the BSFC and reduce the NO_x emissions at the same time.

Tab. IV shows results of the BSFC modeling process for the 12 selected operating points in Tab. II. According to Tab. IV, the root mean squared errors between the measured and the estimated BSFC are relatively small. The coefficient of determination R^2 is an important factor to show how well data is fitted to a statistical model. The closer of R^2 to 1, the better of the fitting result. With models in which more independent variables are carried, the R^2 values will always increase. Hence, another coefficient of determination, the *adjusted coefficient of determination* $R^2_{adjusted}$, is adopted. The $R^2_{adjusted}$ includes the number of degrees of freedom available to estimate the error after calculating the coefficients and thus is safer to use to evaluate the error of a complex model. The goodness of the BSFC fitting is good as all of the R^2 and $R^2_{adjusted}$ are close to 1.

Figure 5 shows an example of the BSFC optimization at 1600 rpm and 45 mg. The optimization is done with three parameters but it is not possible to show the results in 4-D, hence the plots are made with each of the three parameters being kept at their optimum. Though the emission constraints are not shown in these surfaces, it is understood that the NO_x emission, generated at the optimum, satisfied the constraint set in (4). It can be seen that the optimum points are not all located at the minimum points on the surfaces. This is the compensation between the NO_x emissions and the fuel consumption, in order to get lower emissions, more fuel is consumed.

Finally, after conducting the constrained optimization process for all the operating points, the optimized values of each input parameters are presented in scatter plots which

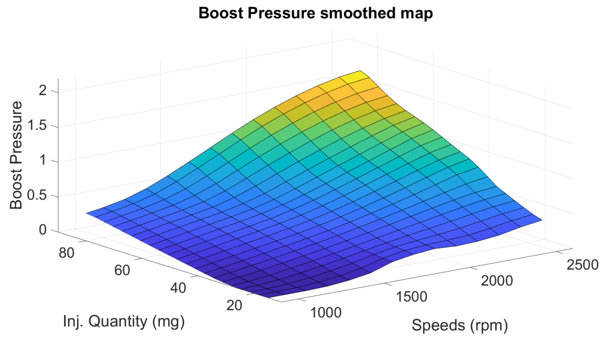


Fig. 6. INTAKE PRESSURE MAP.

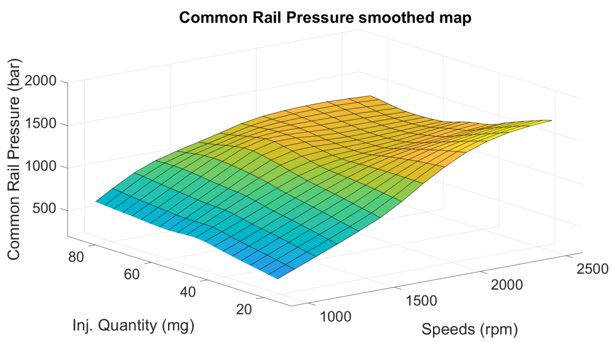


Fig. 7. COMMON RAIL PRESSURE MAP.

are similar to the plot in Fig. 3. The optimal surfaces of the three parameters are then created by using interpolation. They are shown in Fig. 6, Fig. 7 and Fig. 8, respectively.

V. CONCLUSIONS

This paper presents a study of designing static optimal control maps for high efficiency and emission reduction on diesel engine. The study leads to a finding of an engine calibration method which reduces necessary time and resources. The method has also been implemented on a non-road 44 AWI AGCO engine and on a GT-Power simulation model of that engine. Several conclusions were made from this work:

- An off-line parameterization tool which can be used for semi and fully automatic engine tuning was proposed and developed.
- The Design of Experiments method, which is the core component of the off-line tool, provides an organized and economical way of engine calibration. By using this method a considerable amount of time and resources can be saved.
- The engine response is better optimized in comparison to the traditional "brute force" method. Moreover, the response is even optimized under emission constraints to guarantee environmental protection.
- The off-line parameterization tool outputs the optimal control maps with smoothing transitions between the operating points. This smoothening work assures a smooth run for the engine in speed and load changing conditions.

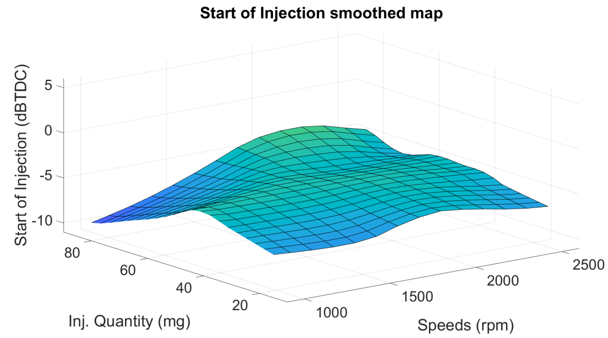


Fig. 8. START OF INJECTION MAP.

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