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## EFFECTIVE COMPONENT TUNING IN A DIESEL ENGINE MODEL USING SENSITIVITY ANALYSIS

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### ABSTRACT

*Error propagation and accumulation is a common problem for system level engine modeling at which individually modeled components are connected to form a complete engine model. Engines with exhaust gas recirculation (EGR) and turbocharging have components connected in a feedback configuration (the exhaust conditions affect the intake and the intake, consequently, affects the exhaust), thus they have a challenging model tuning process. This paper presents a systematic procedure for effective tuning of an engine air-charge path model to improve accuracy at the system level as well as reducing the computational complexity of tuning a large set of components. Based on using sensitivity analysis, the presented procedure is used to inspect which component influences more a set of selected outputs in a model with high degree of freedom caused by many parameters of different components. After selecting the influential component, which is the turbocharger in this study, further tuning is applied to parameters in the component to increase the overall accuracy of the complete engine model. The corrections applied to the air-charge path model of a 6 cylinder 13L heavy duty diesel engine with EGR and twin-scroll turbocharger was shown to effectively improve the model accuracy.*

### NOMENCLATURE

#### VARIABLES

A	Area ( $m^2$ )	$C_p$	Heat capacity (J/kg/K)
F	Burned gas fraction (-)	I	Inertia ( $kg.m^2$ )
$\dot{m}$	Mass flow rate (kg/sec)	M	Torque (N.m)
P	Pressure (Pa)	PR	Pressure ratio (-)
PW	Power (W)	T	Temperature (K)
R	Gas constant (J/kg/K)	r	Comp. wheel radius (m)
$\eta$	Efficiency (-)	$\rho$	Density ( $kg/m^3$ )
$\omega$	Speed (RPM)	$\gamma$	Ratio of $C_p/C_v$ (-)

#### SUBSCRIPTS

c	Compressor	corr	Corrected
dst	Downstream turbine	e	Engine
eff	Effective	EGR	Exh. gas recirculation
eml	Large scroll exh. man.	ems	Small scroll exh. man.
im	Intake manifold	tc	Turbocharger
t	Turbine	upc	Upstream compressor
upt	Upstream turbine	WG	Wastegate

### INTRODUCTION

Control and monitoring strategies in modern engine control units (ECUs) require use of many physical engine variables. The measurement cost or/and the sensibility of measuring a variable at harsh operating conditions of an internal combustion engine limits utilizing sensors on a production engine. Therefore implementation of engine models inside the ECU, instead of addition of sensors, has been a common interest for engine manufacturers. The modeling work can be as simple as simulating

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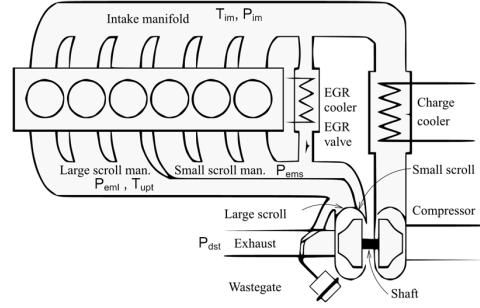
pressure drop over the air filter [1] or as complicated as simulating engine's pollution gas and the emission system [2, 3]. Whatever the model is, a general approach in many developed engine models is physics-based modeling. The development of physical engine models usually follows two steps. The first step, called component level modeling in this paper, comprises modeling individual components based on their inputs and outputs measured at steady state operating conditions. The second step is a system level modeling at which all individual steady-state component models are connected to form a complete engine model. When a complete engine model (i.e. a system level model) is formed by connecting models of individual components, the final accuracy reduces due to reasons such as error accumulation/propagation or mismatch between conditions of data collection for component level modeling and system level model verification (e.g. gas bench conditions used to provide a turbocharger map and conditions on an engine [4]). Therefore an overall parameter tuning at the system level is required to improve the final performance of the complete engine model.

There are many candidates of parameters and components in a complete engine model to be considered in the final tuning process. To reduce the number of the candidates, this paper presents a systematic methodology based on sensitivity analysis (SA) to determine the major component influencing the complete engine model. Sensitivity analysis determines how selected model outputs are affected by a small deviation in an individual component's output. Then a metric is used to quantify the importance of components based on applying the principle component analysis to the sensitivity matrix. When the major influencing component is detected, a fine tuning process is applied to that component which improves performance of the engine model in predicting measured outputs.

## DIESEL ENGINE MODEL

A control-oriented model of the air path of a 13 liters 6-cylinder heavy duty diesel engine, represented by the schematic in Fig. 1, is presented. The considered engine is equipped with an asymmetric twin-scroll turbine which has benefit in increasing exhaust gas recirculation (EGR) while keeping low the back pressure and smoke by mitigating long delays from the EGR path. The engine is also equipped with a wastegate valve, which bypasses the large scroll avoiding over-boosting and reducing the pumping loss.

Model development for this engine has two steps. The first step is the component level where parameters to individually model each component is estimated. At the system level, which is the second step, all components are connected and final structure of the complete engine model is formed. The following subsections describe each step respectively.



**FIGURE 1:** Schematic of the twin-scroll heavy duty diesel engine.

## Component Level Modeling

For the engine schematically shown in Fig. 1, all components (namely: engine block, turbocharger, intercooler, EGR and wastegate) are modeled individually. Inputs and outputs of each component are measured explicitly (except for the wastegate and EGR where their output flows are estimated). The components' models are mainly from the work presented in [5] with few re-estimation of parameters given that the engine considered here is a different model year and has a smaller level of asymmetry in the turbine scroll. Since the turbocharger, EGR and wastegate will be discussed further in later sections of the paper, their models are presented briefly here.

The compressor map provided by the turbo supplier is the main data source for modeling its flow and efficiency at steady state points. Two non-dimensional parameters are defined, the head parameter ( $\Psi$ ) and the flow parameter ( $\Phi$ ) [6] which are used to create a  $\Phi - \Psi$  relation at each compressor speed using a polynomial regression. Then the compressor flow and efficiency can be calculated as:

$$\dot{m}_{c, map} = \theta_c * \pi r^3 \rho \omega_{tc} f_1(\Psi) \quad (1)$$

$$\eta_c = f_2(\Psi) \quad (2)$$

where  $r$ ,  $\rho$ ,  $\omega_{tc}$  are the compressor wheel radius, the inlet air density, the turbo speed and  $f_1$  and  $f_2$  come from regressions correlating  $\Psi - \Phi$  and  $\Psi - \eta$ , respectively. The regression coefficients are calculated by interpolating polynomial coefficients individually found at each compressor rotational speed [7]. The parameter  $\theta_c$  is introduced here to mathematically apply perturbations to the compressor flow as required by the sensitivity analysis. The twin-scroll turbine flow is simulated as a function of the scrolls pressure ratio ( $\frac{P_{dst}}{P_{eml}}$ ,  $\frac{P_{dst}}{P_{ems}}$ ) and the turbo shaft speed ( $\omega_{tc}$ ). The parametric model for the turbine flow can be found with good accuracy using test with closed wastegate at the engine test

bench, unlike the compressor for which the high interaction between the compressor variables (pressure ratio, speed and flow) implies using its characteristic map. The turbine efficiency is calculated by creating a balance between the compressor and the turbine powers:

$$\eta_t = \frac{P W_c}{\dot{m}_t T_{upt} C_p (1 - \frac{P_{dst}}{P_{upt}} \frac{\gamma/\gamma-1}{})} \quad (3)$$

The turbine efficiency calculated from Eq. 3 takes values in the range of [.7 – .8] and it can effectively be approximated as a constant [5]. The EGR flow is modeled using the standard isentropic orifice flow model as:

$$\dot{m}_{EGR} = \theta_{EGR} * A_{eff,EGR} \frac{P_{ems}}{\sqrt{RT_{ems}}} F(PR), \quad PR = \frac{P_{im}}{P_{ems}} \quad (4)$$

in which the parameter  $\theta_{EGR}$  again is a mathematical parameter defined to facilitate implementing the sensitivity analysis within the simulation. The effective area in Eq. 4,  $A_{eff,EGR} = g_{EGR}(u_{EGR}, \omega_e, PR)$ , is a function of ECU command,  $u_{EGR}$ , and also pressure ratio and engine speed which are included to account for the pulsation effects. The same isentropic orifice model is used to simulate the WG flow rate:

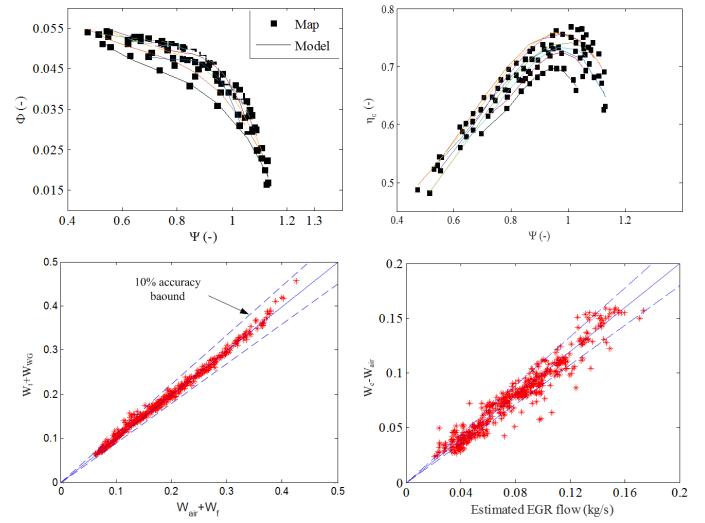
$$\dot{m}_{WG} = \theta_{WG} * A_{eff,WG}(x_{WG}) \frac{P_{eml}}{\sqrt{RT_{eml}}} F(PR), \quad PR = \frac{P_{im}}{P_{eml}} \quad (5)$$

where  $\theta_{WG}$  is the parameter for the sensitivity analysis and  $x_{WG} = g_{WG}(u_{WG}, P_{eml}, P_{dst})$  is the wastegate displacement taken from the wastegate mechanism force balance [5].

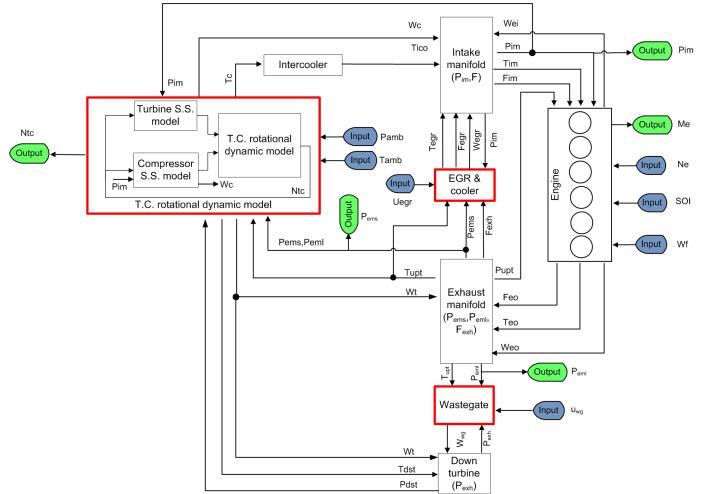
The performance of the components' models are presented in Fig. 2. Figure 2-a,b compares the regression models to the data from the compressor map and in Fig. 2-c,d the modeled wastegate and EGR mass flow rates are compared to their corresponding estimated values collected from tests at a highly instrumented engine test bench [5]. As the plot shows, for most of the operating points, there is good agreement (within a 10% error bound) between the modeled and measured data.

### System Level Modeling

The complete engine model (shown schematically in Fig. 3) is formed by connecting individual components described in the former subsection along with dynamical models for pressure ( $\dot{P}_{im}, \dot{P}_{ems}, \dot{P}_{eml}, \dot{P}_{dst}$ ), air fractions ( $\dot{F}_{im}, \dot{F}_{em}$ ) and the turbocharger speed ( $\dot{\omega}_{tc}$ ) as presented in [5]. Moreover, a temperature dynamical model has been augmented to the airflow dynamics to account for heat accumulation in the engine body [8] which improves the engine model capability to follow very slow dynamics observed in the measured data. The final performance of the complete

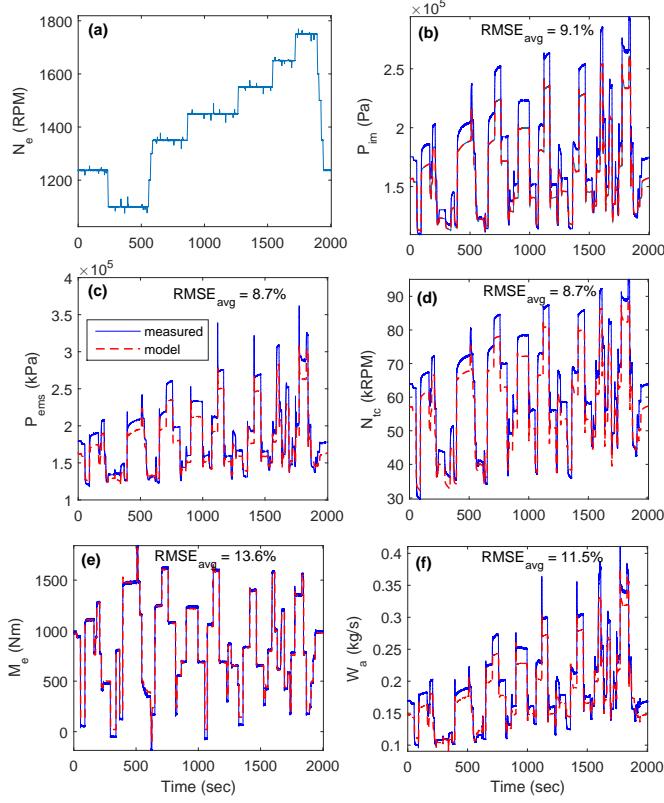


**FIGURE 2:** A summary of modeling results at the component level

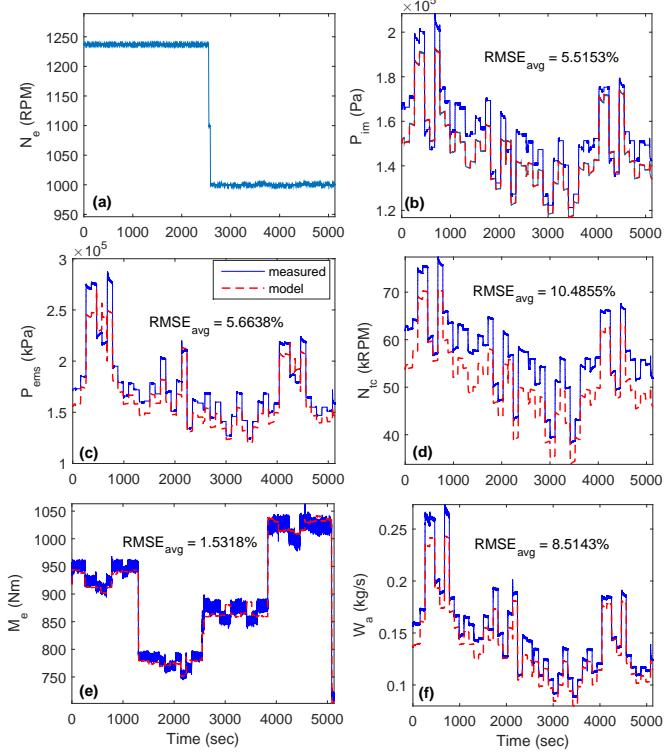


**FIGURE 3:** Overview of the complete engine model, its inputs and selected outputs

model is presented in Fig. 4. As plotted the general trend of the engine model follows that of the measurements. However, steady state offset at different points is clearly observed. The averaged root mean square ( $RMSE_{avg}$ ) in Fig. 4 is defined as the conventional RMSE divided by the average of measured data over the entire time window at each test. To remove the offset, a parameter fine-tuning is required. The question is which components have the most influence and should be tuned. This is decided using the sensitivity analysis as described in the next section.



(a) Test 1



(b) Test 2

**FIGURE 4:** Overall performance of the engine model after connection of all components

## SENSITIVITY ANALYSIS (SA)

When analyzing components in a complete system model, one may investigate how much specific outputs are affected by individual components or, equivalently, how much the complete model is sensitive to a sub-model. This description suggests the use of sensitivity analysis to assess the importance of each component in a system of interconnected elements. Since the sensitivity analysis has well developed notation in terms of parameter sensitivity, here we describe the mathematical formulations for a parameter sensitivity analysis problem that investigates how much each parameter is influencing a model. Then a similar procedure is applied by using the defined parameters  $\theta_c$ ,  $\theta_{EGR}$  and  $\theta_{WG}$  which enable us to treat each respective component as a parameter and thus finding the components' influences on a set of the engine model outputs which is selected here as  $Y = [P_{im}, N_{tc}, P_{ems}, P_{eml}]$ .

The normalized output-to-parameter sensitivity matrix,  $\tilde{S}$ , is defined to contain information about the effect of a system parameters on its outputs. The elements of the sensitivity matrix,  $\tilde{S}_{ij}$  are defined as:

$$\tilde{S}_{ij} = \frac{\tilde{\theta}_j}{\tilde{y}_i} \cdot \frac{\partial \tilde{y}_i}{\partial \tilde{\theta}_j} \quad (6)$$

In Eqn. (6)  $\tilde{y}_i$  is the nominal value for  $i^{th}$  output calculated by using the nominal value for the  $j^{th}$  parameter,  $\tilde{\theta}_j$ , at a specific operating point. The normalization introduced in Eqn. (6) eliminates the effects of magnitude and unit of outputs and parameters. Different approaches can be used to compute the partial derivative  $\partial \tilde{y}_i / \partial \tilde{\theta}_j$  from the model equations [9]. For highly nonlinear dynamic models (as in the engine model here) an efficient technique is to use the finite difference formulation as:  $\partial \tilde{y}_i / \partial \tilde{\theta}_j \approx \Delta \tilde{y}_i / \Delta \tilde{\theta}_j$  with proper selection of the step size  $\Delta \tilde{\theta}_j$  [10]. The locality in the sensitivity analysis (small value for  $\Delta \tilde{\theta}_j$ ) is acceptable in this work since at the fine-tuning stage of a modeling work, the range of all parameters is known and small changes in the parameters are desired.

Based on the defined sensitivity matrix, different techniques can be used for measuring importance of parameters. For example in [11] the average of all outputs sensitivities to each parameter in the sensitivity matrix is used as a measure of importance. Another technique to calculate a quantitative measure for importance is to look at the direction (in the parameter space) at which data from the sensitivity matrix are distributed and selecting a parameter (component in this paper) which has affected the distribution more than others. This can be done by applying Principle Component Analysis (PCA) to the sensitivity matrix  $\tilde{S}$  which calculates eigenvalues (main directions of data distribution) and eigenvectors (variations at each main direction) of the covariance matrix  $X = Cov(\tilde{S})$ . For a  $n \times m$  matrix  $\tilde{S}$  ( $n$  outputs and  $m$  parameters) PCA calculates (maximum)  $n$  orthonormal eigenvectors

tors in a  $m$ -dimensional space. The first eigenvector is the main direction (in the  $m$ -dimensional space) at which data of  $\tilde{S}$  are distributed. Therefor the weight of each element in an eigenvector shows how much the corresponding parameter has contributed to data alignment in that direction [12].

The eigenvectors,  $[C_{1i}, \dots, C_{ji}, \dots, C_{mi}]^T$ , and eigenvalues,  $\lambda_i$ , from PCA of  $\tilde{S}$  are used to calculate the following importance measure for the  $j^{th}$  parameter [13]:

$$\mu_j = \frac{\sum_{i=1}^n |\lambda_i C_{ji}|}{\sum_{i=1}^n |\lambda_i|} \quad (7)$$

with  $0 \leq \mu_j \leq 1$ . As the numerator in Eqn. 7 suggests, the importance of each parameter in a principle direction,  $C_{ji}$ , is multiplied by the direction's importance,  $\lambda_i$ . Since elements of  $\tilde{S}$  represent deviation of outputs due to perturbation in parameters, thus the measure,  $\mu_j$ , shows how much perturbing the  $j^{th}$  parameter has contributed to deviation in the vector of outputs  $Y$ .

The importance measure introduced in Eqn. 7 for parameter analysis is extended here to detect effectiveness of each component (instead of parameters) on the model outputs within the following implementation procedure.

#### Implementation Procedure for SA

- 1- Select the outputs, components and design an operating procedure. This procedure should allow all components (and their outputs) to be practiced in their effective range. Then, simulate the model without perturbing outputs of any component. This provides the base line (nominal) data.
- 2- Select a step size for perturbation in components outputs. The step size should be selected properly to estimate the partial derivative term in Eqn. 6 with finite differences. Perturb the output of one component by the step size and run the model. Use Eqn. 6 to calculate the first column of the sensitivity matrix. Repeat this step for all desired components.
- 3- Run PCA for the sensitivity matrix derived at the last step and then use Eqn. 7 to calculate the importance measure for each component.

#### Using SA For The Engine Model

The 3-step proposed implementation procedure for SA is applied to the heavy duty diesel engine model described in section 2. The first 2 steps calculate the sensitivity matrix and at step 3, the sensitivity of the engine model to each component is calculated. The following describes details of applying the SA to the engine model.

**Step1** The selected output vector is  $Y = [P_{im}, N_{tc}, P_{ems}, P_{eml}]$ . Flow models for the compressor,

the EGR and wastegate are selected to be analyzed for their effect on the output vector  $Y$ . To do this, the parameter vector  $\Theta = [\theta_c, \theta_{EGR}, \theta_{WG}]$  with the initial value of  $\Theta_0 = [1, 1, 1]$  is used to apply perturbations to the components' flows. Two different test procedures were selected, one with major changes in the engine torque and engine speed and the other by major changes in the wastegate and EGR positions (Test 1 and Test 2 in Fig. 4 respectively).

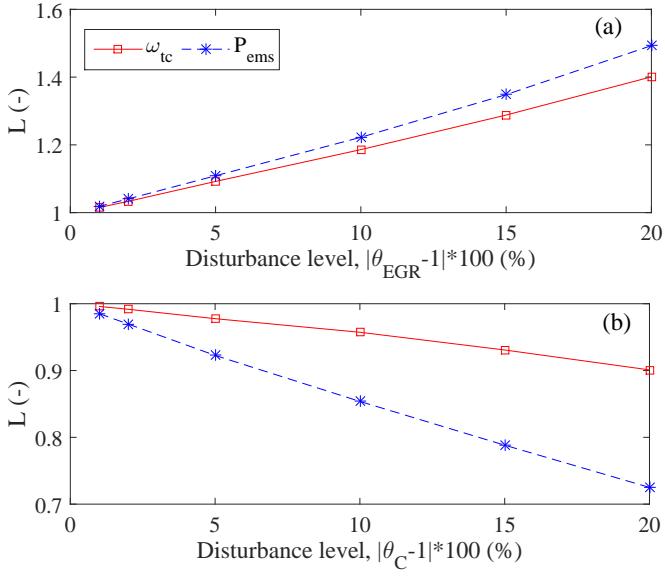
**Step2** To estimate the derivative term in Eqn. 6 with a finite difference,  $\Delta \tilde{y}_i / \Delta \tilde{\theta}_j$ , the step size for  $\Delta \tilde{\theta}_j$  should be properly selected to ensure the required linearity condition (which needs small  $\Delta \tilde{\theta}_j$ ) and to avoid treating noise and computation errors as sensitivities (which needs big  $\Delta \tilde{\theta}_j$ ) [10]. To select  $\Delta \tilde{\theta}_j$ , the following criteria is calculated over a drive cycle time ( $T$ ) to evaluate the linearity:

$$L = \frac{\sum_{t=0}^T \left( \frac{\tilde{\theta}_j \Delta \tilde{y}_i}{\tilde{y}_i \Delta \tilde{\theta}_j}(t) \right)_-}{\sum_{t=0}^T \left( \frac{\tilde{\theta}_j \Delta \tilde{y}_i}{\tilde{y}_i \Delta \tilde{\theta}_j}(t) \right)_+} \quad (8)$$

where  $((\tilde{\theta}_j \Delta \tilde{y}_i) / (\tilde{y}_i \Delta \tilde{\theta}_j))_-$  is deviation in output  $y_i$  due to a negative perturbation (e.g.  $\Theta = [1, .95, 1]$  for 5% negative perturbation in EGR flow model) in the parameter  $\theta_j$  and  $((\tilde{\theta}_j \Delta \tilde{y}_i) / (\tilde{y}_i \Delta \tilde{\theta}_j))_+$  is due to a positive perturbation. Figure 5 shows  $L$  for  $P_{im}$  and  $\omega_{tc}$  at different perturbation levels (defined as  $|\theta_j - 1| * 100$ ) for perturbed EGR and compressor flows. As observed, a 5% perturbation has relatively linear influence while giving enough excitation to the outputs. Using the 5% perturbation for each element in the parameter vector  $\Theta$ , the sensitivity matrix is calculated from Eqn. 6

**Step3** The importance measure  $\mu_j$  is calculated both with on-line and off-line calculations. At on-line approach, at each single simulation step time the sensitivity matrix is calculated from Eqn. 6 and, by using PCA, the corresponding  $\mu_j$ 's are calculated. Figure 6 shows the results for both Test-1 and Test-2. As observed, the turbocharger has the main effect on the outputs (though  $\mu_{\theta_c}$  is close to  $\mu_{\theta_{EGR}}$  in Test-1 which has trajectories with high variations in engine speed and torque). The EGR comes as the second influential component of the air-charge path model and the wastegate shows the least influence on the model. One reason for higher EGR influence (compared to WG) is that changing the EGR affects both the turbine and engine flows directly while the WG only has a direct effect on the turbine flow.

For off-line calculation of the importance measures, the sensitivity matrices calculated form Eqn. 6 at each step time are averaged over the whole range of a test procedure. In addition, the operating points at which a component does not have any flow (such as when the wastegate is closed) were removed from the



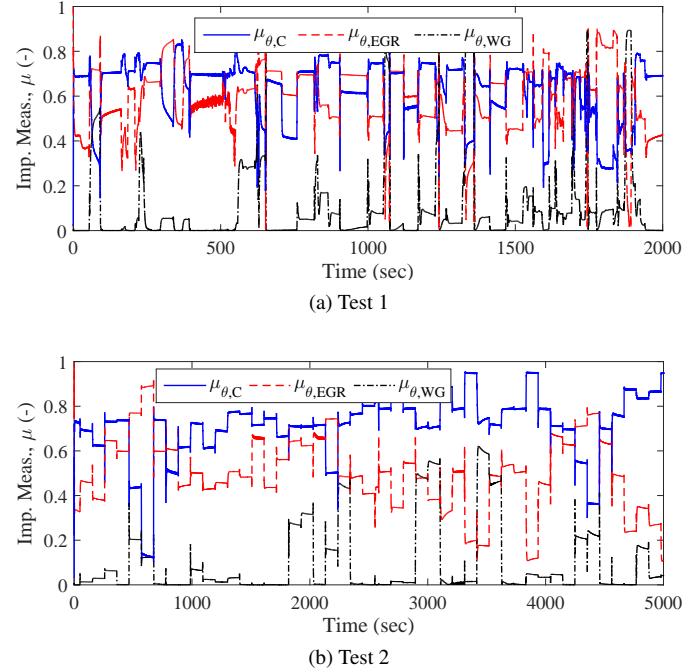
**FIGURE 5:** Linearity analysis with disturbance applied to the EGR and compressor flows

averaging procedure. Figure 7 shows the results for the off-line analysis. An interesting result from Fig 7 is that when the wastegate and EGR are swept (i.e. Test-2) their effect is relatively closer compared to the test (Test-1) at which there is no specific pattern for actuating (exciting) these two components. Thus, depending on the test cycle, each component may be found with different importance for the model designer.

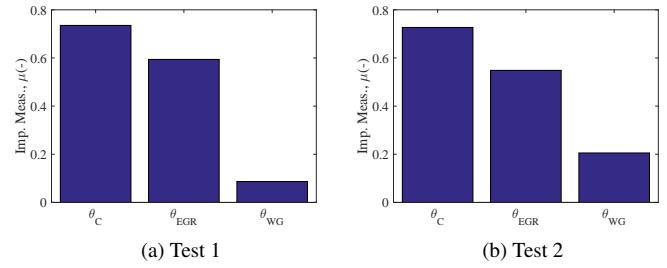
### TUNING THE ORIGINAL MODEL

From the sensitivity analysis it was found that the compressor flow used in the turbocharger dynamical model is the key flow influencing the complete engine model. The compressor flow is a function of its pressure ratio and rotational speed which both have estimation errors as Fig. 4 shows. Even if the pressure ratio and the rotational speed are estimated accurately, there would be deviations between the compressor characteristic map data provided by a turbo supplier and the one measured when it is integrated into an engine air path system. Therefore the tuning procedure should reduce the estimation error for three variables; compressor pressure ratio, rotational speed and air flow. To do so, the turbocharger dynamical model is parameterized as:

$$I_{tc}\omega_{tc}\dot{\omega}_{tc} = \alpha_1\dot{m}_t T_{upt} C_{p,t} \left(1 - \frac{P_{dst}}{P_{upt}}^{(1-1/\gamma)}\right) - [\alpha_2\dot{m}_{c,map} + \alpha_3] T_{upc} C_{p,c} \left(\frac{P_{im}}{P_{upt}}^{(1-1/\gamma_c)} - 1\right) \quad (9)$$



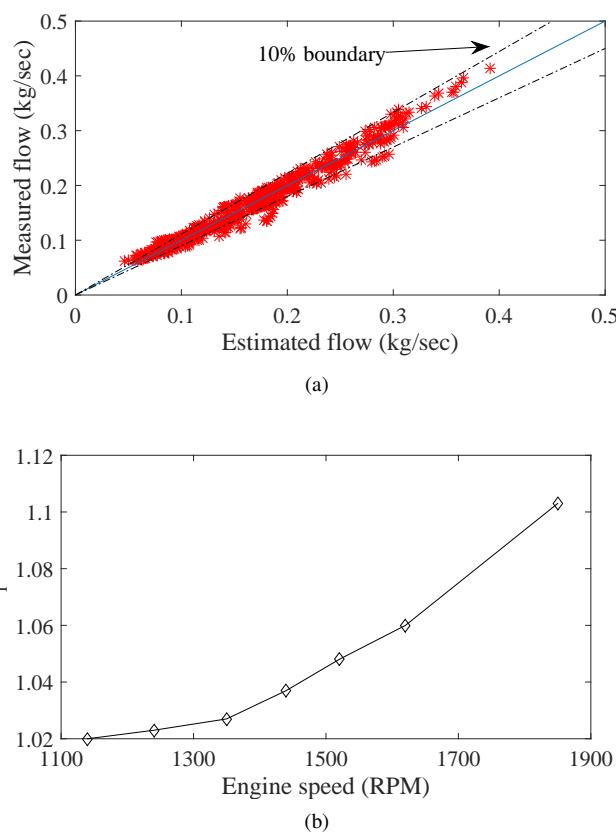
**FIGURE 6:** Importance measure for different components from the on-line analysis



**FIGURE 7:** Importance measure for different components from the off-line analysis

In Eqn. 9,  $\alpha_1$  is included to cancel the inaccuracy in the turbocharger efficiency caused by pulsation and heat transfer which happen during the engine operation and  $\alpha_2$  and  $\alpha_3$  correct the compressor flow model. An optimization problem can be defined to calculate these three parameters as the following:

$$\begin{aligned} [\alpha_1, \alpha_2, \alpha_3] = \arg \min_{\alpha_1, \alpha_2, \alpha_3} & \left\| \frac{P_{im,meas} - P_{im}}{P_{im,meas}} \right\|^2 + \left\| \frac{\omega_{tc,meas} - \omega_{tc}}{\omega_{tc,meas}} \right\|^2 + \\ & \left\| \frac{\dot{m}_{c,meas} - \dot{m}_c}{\dot{m}_{c,meas}} \right\|^2 \end{aligned} \quad (10)$$



**FIGURE 8:** (a) Comparison between measured and estimated compressor flow. (b)  $\alpha_1$  as a function of the engine speed.

where  $P_{im}$  is the estimated intake manifold pressure from the filling dynamics and

$$\dot{m}_c = \alpha_2 \dot{m}_{c, map} + \alpha_3 \quad (11)$$

It is difficult to solve the optimization problem for all three parameters simultaneously from Eqn. 10 subjected to the nonlinear engine equations. Instead, a specific procedure is proposed here to tune all three parameters within a 2-step solution as described in the following.

### Step1: Tuning the Compressor Flow Model

At the first step,  $\alpha_2$ ,  $\alpha_3$  used to apply the bi-linear correction to the compressor flow model were estimated using linear least square method to remove the compressor flow error defined as:  $e_{mc} = \dot{m}_{c,meas} - \dot{m}_c$  using measurements collected during the engine mapping tests. The compressor flow corrected by  $\alpha_2 = 0.9$  and  $\alpha_3 = -0.027$  is compared to the measured air flow in Fig. 8-(a). As shown, the model matches the measured data within the 10% accuracy bound as plotted.

### Step2: Tuning the turbocharger efficiency

The compressor model from Step1 assures that if  $P_{im}$  and  $\omega_{tc}$  are estimated accurately, the compressor air flow from Eqn.11 would be accurate as well. Therefore, the optimization problem defined in Eqn. 10 is reduced to:

$$\alpha_1 = \arg \min_{\alpha_1} \left\| \frac{P_{im,meas} - \hat{P}_{im}}{P_{im,meas}} \right\|^2 + \left\| \frac{\omega_{tc,meas} - \hat{\omega}_{tc}}{\omega_{tc,meas}} \right\|^2 \quad (12)$$

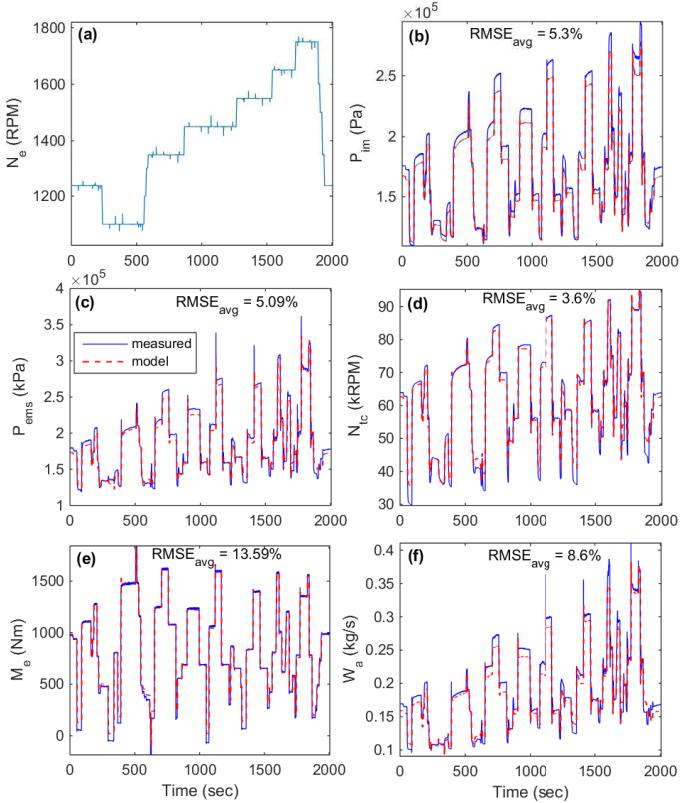
Equation. 12 is solved numerically using the steepest descent algorithm over drive cycles different to what is shown in Fig. 4 in which the engine speed was kept constant and calculated  $\alpha_1$  is tabulated as shown in Fig. 8-(b). Final results of the model with applied corrections to the turbocharger model are shown in Fig. 9 within test procedures similar to those shown in Fig. 4. Compared to Fig. 4, both test cycles show noticeable accuracy improvements for all variables except the engine torque. The reason for this observation is that in a diesel engine, torque is mainly affected by the amount of injected fuel [5].

### CONCLUSION

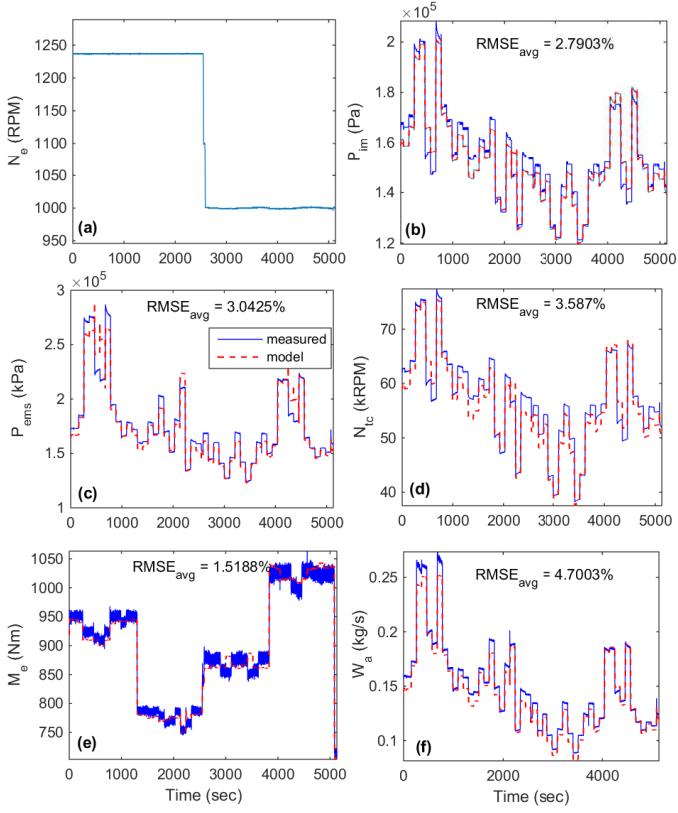
A new methodology to detect main elements in a complete engine model was presented in this paper. A heavy duty 6-cylinder engine model with high pressure EGR was developed at first. For the modeling, each component was modeled individually using data from steady state engine tests and then the complete engine model was formed by connecting component models. Despite the fact that individual component models had acceptable accuracy, noticeable offset from measured data was observed when the complete engine model was simulated. To further tune the model, sensitivity analysis was used to determine how much specific components affect the complete engine model and select the most influential one. This was done by principle component analysis of the sensitivity matrix and use of a measure for quantifying the importance. It was found that the turbocharger was the main component among selected ones. Moreover, the importance measure was found dependent on the selected test procedure by showing different levels of importance for each selected component at different test procedures. Final tuning was applied to the turbocharger model in a two step procedure showed remarkable improvement of the complete engine model.

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(a) Test 1



(b) Test 2

**FIGURE 9:** Performance of the tuned engine model

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