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Selection and Tuning of a Reduced Parameter Set for a Turbocharged Diesel Engine Model

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Abstract— **This paper presents an approach for systematic reduced-parameter-set adaption applicable to internal combustion engine models. The presented idea is to detect the most influential parameters in an engine air-charge path model and then use them as a reduced-parameter-set for further calibration to improve the model accuracy. Since only most influential parameters (in comparison with a complete set of parameters) are tuned at the final calibration process, this approach helps reducing over-parameterization associated with tuning highly nonlinear engine models. Detection of the influential parameters is done using the sensitivity analysis followed by the principle component analysis. Accuracy of the reduced-parameter-set tuned model is compared to a model with a tuned full-parameter-set developed following commercially available OnRAMP Design Suite [1] methodology. Results from experiments on a heavy duty diesel (HDD) engine show that although tuning the full-parameter-set (with over 70 parameters) creates higher accuracy, an average of 50% improvement of the model accuracy is attained using the proposed reduced-parameter-set approach (which tunes only 2 parameters).**

I. INTRODUCTION

Models for simulation of the gas exchange process in an internal combustion engine have found many applications for monitoring and control in modern engine control units (ECUs)[2], [3]. Having a simple structure and low computational burden, the Mean Value Modeling (MVM) is the main concept used in commercialized ECUs which, on the other hand, requires extensive calibration efforts to ensure accurate tracking of variables.

Physics-based modeling and automatic calibration using software tools such as OnRAMP used in this work, are solutions to reduce calibration work on an engine model. In this paper a new approach is proposed and elaborated in which, while doing physics-based modeling, only the main affecting parameters of a complete engine model is detected and tuned. To detect the most influential parameters, the sensitivity analysis followed by the principle component analysis is utilized. Since only the main influencing parameters go to the final tuning process, it is computationally much easier and is realized here using a Kalman filter. The implemented discrete Kalman filter identifies the influential parameters, which are mapped as functions of speed and load, at different engine operating points over drive cycles. Finally, a similar engine model is developed in OnRAMP design suite where the model is with a full set of tunable parameters. The *"fully parameterized"* highly accurate model developed in OnRAMP is used by industry for offline development and calibration of controllers and is utilized in this work as the reference showing the expected level of accuracy for an engine model. Both reduced-parameter (approach of this paper) and full-parameter (approach of OnRAMP) tuned models are compared to experimental data from a heavy-duty diesel (HDD) engine. The reduced-parameter-set tuning technique is shown to halve the estimation error of the engine model and approach the accuracy of the highly accurate reference model developed in OnRAMP. In addition to [12], this paper presents complete parameterization of the component models, results of a realized discrete Kalman filter for online parameters tuning and a comparison to the reference OnRAMP model.

In section II, the engine model is described both at component and engine levels. In section III, an assessment of the parameter's importance is presented using sensitivity and principle component analysis. Then, results of reduced-parameter-set and full-parameter-set tuning are compared in section IV. Finally, the conclusion comes in section V.

II. HDD DIESEL ENGINE MODEL

A 13 liters 6-cylinder heavy duty diesel (HDD) engine with high pressure cooled exhaust gas recirculation (EGR) and a wastegate controlled asymmetric twin-scroll turbine is studied in this paper. The asymmetric twin-scroll turbine has benefit in increasing EGR while keeping low back pressure and smoke [4]. The engine is also equipped with a wastegate valve, which bypasses the large scroll avoiding over-boosting and reducing the pumping loss.

The model development presented for this engine has two steps. The first step is a component-level modeling where parameters for individual models of components are estimated. At the engine level, which is the second step, all components are connected and the final complete engine model is formed. The following subsections describe each step respectively.

A. Component Models

For the HDD engine, 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 which its output flow is estimated). The modeling approach for components is similar to the work presented in [4] with re-estimation of parameters given that the engine considered here is a different model year and has a smaller level of

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asymmetry in the turbine scroll. Since the turbocharger, EGR and wastegate are discussed in later sections of the paper, their detailed equations are described here. The reason for selecting these three components is higher uncertainty associated with their modeling equations compared to other engine sub-models. The EGR and turbine uncertainties come from flow pulsations, the compressor is effected by the heat transfer from the turbine and the WG flow model is uncertain since it is not measured but estimated [5].

Turbocharger speed, N_{tc}, comes from its rotational dynamics written by:

$$I_{tc}N_{tc}\dot{N}_{tc} = \tilde{\eta}_t\eta_m\dot{m}_tT_{em}C_{p,t}(1-\frac{P_{ex}}{P_{em}}^{(1-1/\gamma_t)})- \tilde{\dot{m}}_cT_{in}C_{p,c}(\frac{P_{im}}{P_{in}}^{(1-1/\gamma_c)}-1)/\eta_c \tag{1a}$$

$$\tilde{\eta}_t = \theta_T * \eta_t \tag{1b}$$

$$\tilde{\dot{m}}_c = \theta_C * \dot{m}_c \tag{1c}$$

in which η_m and η_c are mechanical and compressor efficiency, $\dot{m}_t$ is the turbine flow, T_{em} and P_{em} are the temperature and pressure in the exhaust manifold, P_{ex} is pressure in the exhaust pipe, C_p is specific heat, T_{in} and P_{in} are the compressor inlet temperature and pressure, P_{im} is the intake manifold pressure, γ is the ratio of specific heats of the gas and r_c is the impeller radius. θ_T and θ_C are mathematical parameters included in the turbocharger model to scale the turbine efficiency, η_t, and the compressor flow, $\dot{m}_c$, and are used for the sensitivity analysis described in Section 3.

The scaled EGR flow, $\tilde{\dot{m}}_{EGR}$, is modeled using the standard isentropic orifice flow model as:

$$\tilde{\dot{m}}_{EGR} = \theta_{EGR} * A_{EGR}\frac{P_{ems}}{\sqrt{RT_{ems}}}F(\frac{P_{im}}{P_{ems}}) \tag{2}$$

in which the parameter θ_{EGR} again is defined for implementing the sensitivity analysis within the simulation and P_{ems} is the exhaust manifold pressure at the turbine's small scroll. The effective area in (2), $A_{EGR} = g_{EGR}(u_{EGR}, N_e, PR)$, is a function of ECU command (u_{EGR}), the pressure ratio ($PR = P_{im}/P_{ems}$) and the engine speed (N_e) which are included to account for the pulsation effects. The EGR flow measured on the engine test bench is used to tune parameters in (2). The same isentropic orifice model is used to simulate the WG flow and scale it as:

$$\tilde{\dot{m}}_{WG} = \theta_{WG} * A_{WG}(x_{WG})\frac{P_{eml}}{\sqrt{RT_{eml}}}F(\frac{P_{im}}{P_{eml}}) \tag{3}$$

where θ_{WG} is the scaling parameter for sensitivity analysis and P_{eml} is the exhaust manifold pressure at the turbine's large scroll. $x_{WG} = g_{WG}(u_{WG}, P_{eml}, P_{ex})$ is the wastegate displacement taken from the wastegate mechanism force balance which also depends on the ECU command to the WG valve, u_{WG}[5].

B. Complete Engine Model

The complete engine model (shown schematically in Fig. 1) is formed by connecting individual steady state components models (three of them were reviewed in the former subsection) along with dynamical models for pressures ($\dot{P}_{im}$, $\dot{P}_{ems}$, $\dot{P}_{eml}$, $\dot{P}_{ex}$), air fractions ($\dot{F}_{im}, \dot{F}_{em}$) and the turbocharger speed ($\dot{N}_{tc}$) with details presented in [4]. The final performance of the complete HDD engine model is presented in Fig. 2 over three different drive cycles (DCs) in which different trajectories for the engine speed, torque, EGR and WG were used. As plotted the general trend of the engine model follows that of the measurements however, steady state errors clearly exist. The averaged root mean square ($RMSE_{avg}$) used in Fig. 2 is defined as the conventional RMSE divided by the average of measured data over the entire time window at each test. A final tuning of the engine model parameters is a typical step to reduce the estimation error but, computationally, it is difficult to tune all parameters in the complete engine model. In the next section, the sensitivity analysis is used to detect parameters in the complete HDD engine model whose tuning has the most improvement in a set of selected outputs.

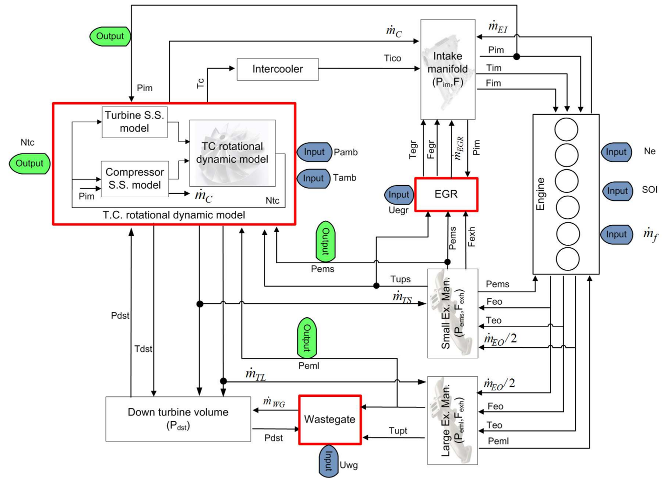


Fig. 1: Overview of the complete engine model, its inputs and selected outputs.

III. PARAMETER IMPORTANCE DETECTION

Importance of the defined scaling parameters θ_T, θ_C, θ_{EGR} and θ_{WG} is calculated by detecting their influence on a set of the engine model outputs which is selected here as $Y = [N_{tc}, P_{im}, P_{ems}, P_{eml}]$. The influence is detected using parameter sensitivity analysis which uses the normalized output-to-parameter sensitivity matrix ,$\tilde{S}$, 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:

$$\tilde{S}_{ij} = \frac{\tilde{\theta}_j}{\tilde{y}_i}.\frac{\partial\tilde{y}_i}{\partial\tilde{\theta}_j} \tag{4}$$

In (4) $\tilde{y}_i$ 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 (4) 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 [6]. For highly nonlinear dynamic models (as in our case) an efficient technique is to use the finite difference formulation

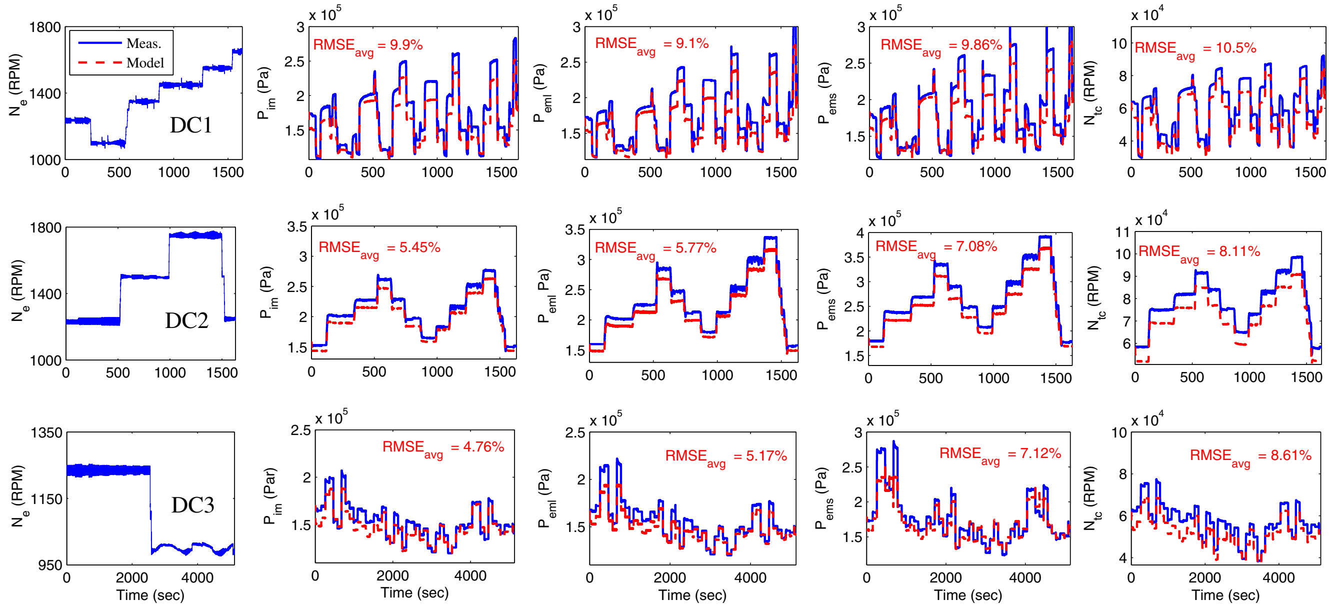


Fig. 2: Simulated outputs of the complete HDD engine model compared to measured data for three drive cycles (DC).

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 $\Delta\tilde{\theta}_j$. Although, small values for $\Delta\tilde{\theta}_j$ make the finite difference assumption more accurate, but computational noise would affect the final results [7]. Moreover, the locality in the sensitivity analysis (small value for $\Delta\tilde{\theta}_j$) is acceptable in this work since the case is that at the fine-tuning stage of a modeling work, the range of all parameters is known and small changes in the parameters are desired.

The sensitivity of the selected output vector to the scaling parameters vector $\Theta = [\theta_T, \theta_C, \theta_{EGR}, \theta_{WG}]$ is calculated and results are shown in Fig. 3 for all variables in the selected output vector. As observed, θ_T has the most influence in all outputs. But for other three parameters, based on the selected output, each parameter has different level of influence. For example, θ_C is the main parameter influencing the turbo speed (Fig. 3-a) while θ_{EGR} effects P_{ems} more than the other two parameters (Fig. 3-c). This output-based influence requires a metric which utilizes all sensitivities and makes a decision on the importance of a parameter on an output vector. As an example, in [8] 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 is distributed and selecting a parameter 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 in our SA case study) PCA calculates (maximum) n orthonormal eigenvectors in a m-dimensional space. The first eigen-

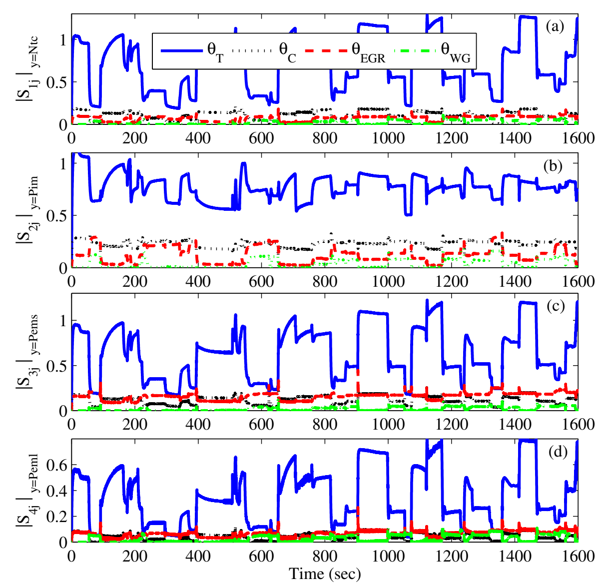
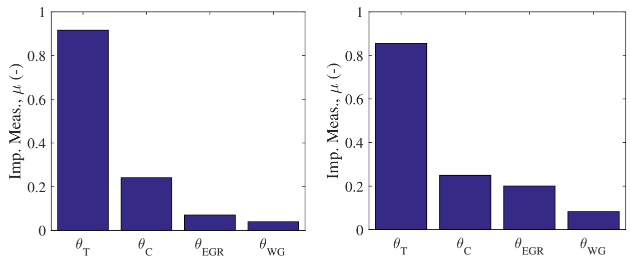


Fig. 3: Sensitivity of air-charge path variables to different parameters

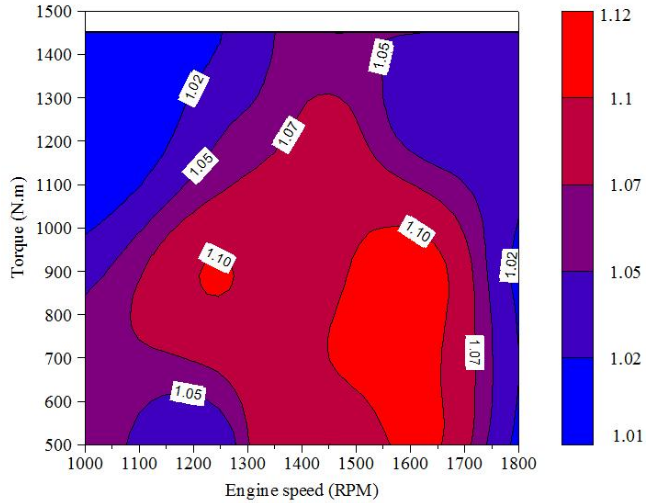
vector is the main direction (in the m-dimensional space) at which data of $\tilde{S}$ are distributed. Therefore the weight of each element in an eigenvector shows how much the corresponding parameter has contributed to data alignment in that direction[9]. The eigenvectors, $[C_{1i}, ..., C_{ji}, ..., C_{mi}]^T$, and eigenvalues, λ_i, from PCA of $\tilde{S}$ are used to calculate the following importance measure for the $j^{\ th}$ parameter[10]:

$$\mu_j = \frac{\sum_{i=1}^{n} |\lambda_i C_{ji}|}{\sum_{i=1}^{n} |\lambda_i|} \tag{5}$$

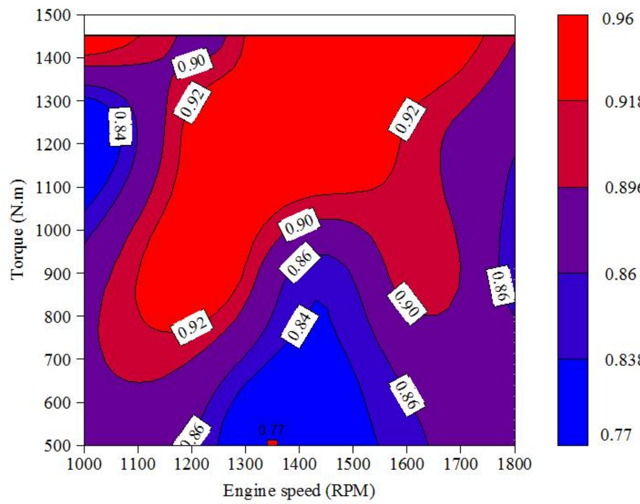


(a)- DC1 (b)- DC3

Fig. 4: Importance measure for different parameters from the off-line analysis



(a) Parameter θ_T



(b) Parameter θ_C

Fig. 5: Contour plots of estimated θ_T and θ_C estimated over DC1 and DC2.

with $0 \leq \mu_j \leq 1$. As the numerator in (5) suggests, the importance of each parameter in a principle direction, C_{ji}, is multiplied by the direction's importance, λ_i. Since elements of $\tilde{S}$ represent deviation of outputs due to perturbation in parameters, thus the measure, μ_j, shows how much perturbing the j^{th} parameter has contributed to deviation in the vector of outputs, Y [11].

The importance measure introduced in (5) for parameter analysis is applied here to detect effectiveness of each parameter on the engine model outputs with details described in [12]. Two different test procedures were selected, one with major changes in the engine torque and engine speed and the other with major changes in the wastegate and EGR positions (DC1 and DC3 in Fig. 2 respectively). To calculate the importance measures, the sensitivity matrices calculated from (4) at each step time are stacked over a test procedure and then PCA is applied to the final matrix. Fig. 4 shows the results for the two drive cycles. As observed, at both DC1 and DC3, θ_T (as is expected) has the main effect on the outputs (though μ_{θ_T} is lower in DC3 which has trajectories with high variations in engine EGR and WG). The parameter θ_C comes as the second influential parameter of the air-charge path model, θ_{EGR} as the third and the wastegate shows the least influence on the model. One reason for higher EGR influence (compared to WG) is that changing the EGR effects both the turbine flow and the engine air-fuel-ratio while the WG only effects the turbine flow. Another interesting result from Fig 4 is that when the wastegate and EGR are swept (i.e. in DC3) their effect is relatively higher compared to the test (DC1) at which there is no specific pattern for actuating (exciting) these two components. Thus, depending on the test cycle, each parameter may have different importance for the model designer.

IV. Parameter Tuning and Results

A. Reduced-Parameter-set Tuning

Having θ_T and θ_C selected as the most influential parameters, a discrete Kalman filter is realized for identification of the parameters over drive cycles DC1 and DC2 with measured N_{tc} and P_{im} as feedback variables. The identified parameters (mapped as functions of speed and load) are shown in Fig. 5. As shown, θ_T (ranges in $[1.01-1.12]$) has lower variation than θ_C (ranges in $[0.77-0.96]$) which agrees with $\mu_{\theta T} > \mu_{\theta C}$. This is explained using (1) as, a $\theta_T > 1$ increases N_{tc} and (from the compressor map and the intake manifold filling dynamics) $\dot{m}_c$ and P_{im} consequently. This monotonic effect helps to decrease estimation errors in the Kalman filter quickly since the original model underestimates both N_{tc} and P_{im} (Fig. 2). But θ_C does not effect N_{tc} and P_{im} monotonically since a $\theta_C > 1$ increases the compressor flow which in turn could be balanced by slowing down N_{tc}. Fig. 5 also shows smooth change of parameters over the engine speed and load range. This is required for linear interpolation inside the maps to calculate θ_T and θ_C for operating points not visited during the identification step.

B. Full-Parameter-Set Tuning in OnRAMP

The OnRAMP Design Suite [13], [1], [14], [15] provides a systematic approach to control design process starting from system modeling. It makes the modeling process more efficient and less dependent on the skill level of the engineer. The tool provides environments for building engine scheme out of engine elements library, design of experiment, data management, data analysis and fully automated model calibration based on experimental data and component data such as turbocharger maps. Further, the tool has model validation features and both the local performance of the individual components and the global input-output behavior of overall connected model can be evaluated.

The followings are three main steps carried out to develop and calibrate a reference model in OnRAMP:

1- Setting up the model structure by using the elements library. Also the same data sets as those used for component modeling (Section II-A) are included for model identification.
2- Steady state identification of the model in two steps. At first, a component-level identification is performed that provides reasonable starting points for a global identification. Then, the global identification is done that reconciles the tuning of components in order to achieve very high accuracy of the overall input-output model with interconnected components.
3- Transient identification of the engine model. Parameters such as time constants of actuators and rotational inertia of the turbocharger are identified in this step.

It is recommended to collected data based on a design of experiment (DoE) which is implemented in OnRAMP if a user desires it. However even data collected without a DoE (as done in this work), can be used for modeling in OnRAMP. The 3-step identification scheme has shown successful results for optimally solving complex model identification problems. In the case of the HDD engine model developed in OnRAMP, 79 parameters were taken to the final (global) identification stage which include pressure, temperature, speed and emission models. Out of this 79 parameters, 47 of them are associated with turbocharger and other sub-models with pressure outputs. The optimization problem for the identification is to reduce a quadratic cost function from estimation errors subjected to both dynamic and static constraints which OnRAMP solves it by employing an optimization algorithm based on nonlinear least squares for model identification [13]. OnRAMP can be used on engines of displacements from 1.2L to 15L and consequently it is important to get component local parameters in a feasible initial range so that good performance of the identification procedure is achieved and unnecessary user intervention avoided [13]. This initial range is calculated at the component level identification stage.

C. Comparing Reduced and Full-Parameter-Set Tuning

The final tuned models are tested in the three DCs used to test the original HDD engine model (shown in Fig. 2). It is worth noticing that DC3 is not used during the parameter identification process. Results are shown in Fig. 6 in which experimental measurements and OnRAMP simulated data are also included. Compared to Fig. 2, the averaged RMSE is reduced in all drive cycles for the model with tuned reduced-parameter-set (indicated as "Reduced" in Fig. 6). Moreover, as shown, the full-parameter-set model identified by OnRAMP has better accuracy for all variables except the small exhaust manifold pressure (P_{ems}). A reason for this problem is that EGR valve position was not swept enough in the dataset used for setting up the engine model in OnRAMP.

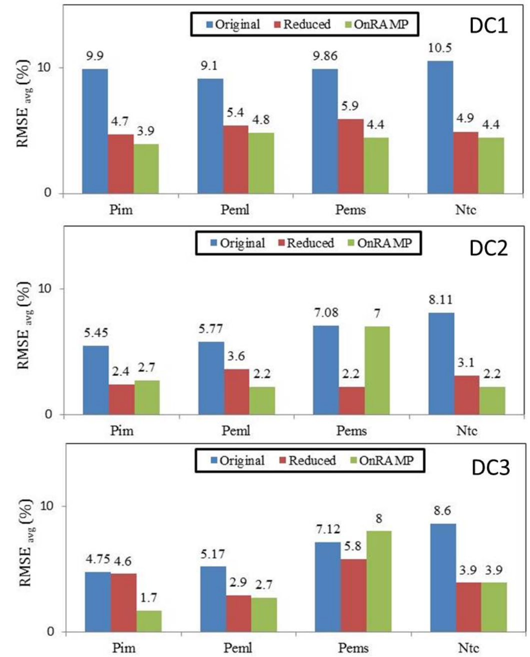


Fig. 7: Comparison of models accuracy in three different drive cycles (DCs).

Fig. 7 shows a summary of accuracy of the three models discussed in this paper. As shown, by reduced-parameter-set tuning, accuracy of estimation for all variables has improved noticeably, with N_{tc} attaining the highest improvement. Predictive ability of the "Reduced" model is also good as for DC3 (which has not been used during parameter tuning) accuracy has improved, even with lower final values compared to DC1 and DC2. However, as shown in Fig. 7, the OnRAMP model has the highest accuracy for all variables (except P_{ems}) which is attained through full-parameter-set tuning. Therefore, the reduced-parameter-set tuning approach is recommended in applications requiring on-line model tuning where moderate accuracy along with simplicity is mandatory and where the high accuracy needs to be sacrificed due to heavy computational load.

V. CONCLUSIONS

Reduced-parameter-set tuning was addressed in this paper for the gas exchange path model of a HDD engine. To make the reduced-parameter-set adaption possible, the main idea was to tune only parameters with the highest influence on the model. The influential parameters were detected using four parameters added to the engine model such that the sensitivity of selected outputs was analyzed to flow of the EGR, wastegate and compressor as well as the turbine efficiency. Since the outputs were not showing a unique sensitivity to all parameters, a metric to quantify the overall sensitivity of all outputs to a parameter was used based on principle component analysis. After the turbine efficiency and the compressor flow were detected to be the most influential, their scaling parameters were tuned in a final identification

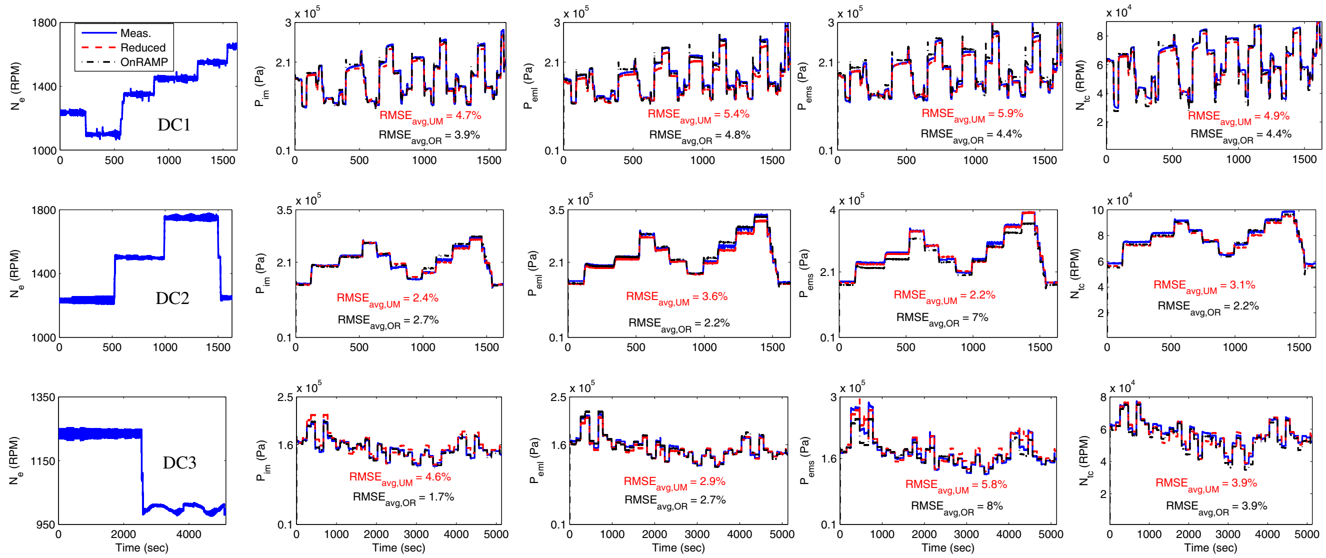


Fig. 6: Measured outputs compared to those simulated by the tuned model and by the model developed in OnRAMP

step. A discrete Kalman filter was implemented and the parameters (mapped as functions of speed and load) were identified over two drive cycles. The reduced-parameter-set tuned model was tested against experimental measurements on a HDD engine as well as a model developed in OnRAMP Design Suite which tunes a full set of parameters in an engine model. Results from different test drive cycles showed tuning reduced number of parameters (only 2 parameters in the turbocharger model) improves the model accuracy more than 50% in average. This made the tuned model to successfully approach to the highly accurate model tuned by OnRAMP.

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