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GAUSSIAN PROCESS REGRESSION FEEDFORWARD CONTROLLER FOR DIESEL ENGINE AIRPATH

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ABSTRACT−Gaussian Process Regression (GPR) provides emerging modeling opportunities for diesel engine control. Recent serial production hardwares increase online calculation capabilities of the engine control units. This paper presents a GPR modeling for feedforward part of the diesel engine airpath controller. A variable geotmetry turbine (VGT) and an exhaust gas recirculation (EGR) valve outer loop controllers are developed. The GPR feedforward models are trained with a series of mapping data with physically related inputs instead of speed and torque utilized in conventional control schemes. A physical model-free and calibratable controller structure is proposed for hardware flexibility. Furthermore, a discrete time sliding mode controller (SMC) is utilized as a feedback controller. Feedforward modeling and the subsequent airpath controller (SMC+GPR) are implemented on the physical diesel engine model and the performance of the proposed controller is compared with a conventional PID controller with table based feedforward.

KEY WORDS : Gaussian process regression, Feedforward control, Discrete time sliding mode control, Airpath control

P_i : nomenclature
P_x : intake manifold pressure
P_c : exhaust manifold pressure
P_a : compressor power
R : ambient pressure
R : ideal gas constant
T_i : intake manifold temperature
T_x : exhaust manifold temperature
T_a : ambient temperature
V_i : intake manifold volume
τ : turbocharger time constant
W_{ci} : compressor mass airflow
W_{xi} : exhaust gas recirculation mass flow
W_{ie} : engine inlet gas mass flow
W_{xt} : turbine inlet gas mass flow
W_f : fuel mass flow
η_c : isentropic compressor efficiency
η_T : turbine total efficiency
c : specific heat of air
u_{ff} : feedforward control term
u_{fb} : feedback control component
Ar_{EGR} : exhaust gas recirculation valve area
h_{xt} : exhaust gas enthalpy
u_1 : controlled input 1, area of EGR
u_2 : controlled input 2, area of VGT
μ : isentropic ratio
r_{VGT} : VGT vane position
r_{EGR} : EGR valve position

1. INTRODUCTION

Emissions control is probably the most challenging part of the current diesel engine development process. Most harmful kinds of exhaust emissions are nitrogen oxides (NO_x), particulate matter (PM) and hydrocarbons (HC). Tailpipe emissions are results of aftertreatment and engine out (feed gas) emissions. Aftertreatment system is composed of catalysts, filters and auxiliaries which are designed for preventing release of harmful engine out emissions to the atmosphere. Engine out emissions are results of combustion of air and fuel mixture in cylinders of an internal combustion engine. Airpath control determines total mass of air sucked into the cylinders and its composition in terms of fresh air and exhaust recirculation gas. On the other hand, tailpipe emissions are results of catalyst helped reagent reactions to form nontoxic gases from toxic engine out emission gases. Particle emissions to the atmosphere are avoided via particulate filter which is emptied via burning trapped soot. Catalyst efficiencies and particulate filter regeneration performances are associated with gas flow rate and temperature. Flow is a direct controlled output of airpath and temperature is indirectly affected by airpath control. Both tailpipe and engine out emissions are closely related to the engine airpath control performance. Exhaust gas recirculation (EGR) system is a major engine

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out NO_x reduction element in diesel engines (Heywood, 2000). Higher combustion temperature favors NO_x formation. Combustion temperature reduction requires lower oxygen concentration and increased gas heat capacity which are mainly achieved by utilization of the EGR. However, lower temperature and reduced oxygen concentration boosts formation of PM or HC. The described trade-off emphasizes the importance of precise airpath control.

Fresh air is pumped to the engine via turbocharger. Modern diesel engines utilize geometry turbochargers (VGT) for higher boost build up performance and optimized pumping loss. Turbocharger harvests the waste heat after exhaust stroke and uses the energy for pumping air into the engine. VGT actuator governs the energy that is being harvested through the turbine and changes the exhaust manifold and intake manifold pressures. EGR line gas flow is driven by the pressure difference between intake and exhaust manifolds and shares the total exhaust flow with the turbine. As a result, VGT and EGR systems are closely coupled. Also the airpath has non-minimum phase behavior which creates challenge in obtaining inverse models (Kolmanovsky, 1997).

Although selection of output is another line of research examined by several authors (e.g. Nieuwstadt *et al*., 2000; Wahlstrom and Eriksson, 2013), mass air flow (MAF) through compressor and manifold air pressure (MAP) are the common selection of controlled outputs of diesel engine airpath. In the practical applications, desired values of MAF and MAP signals are interpolated from predefined (calibrated) tables whose axes are speed and injected fuel quantity or desired inner torque. When one neglects low pressure EGR or multi turbocharger configurations, diesel engine airpath control problem can be defined as tracking MAF and MAP desired values via manipulation of EGR and VGT actuators despite disturbances of other engine dynamics.

Due to its complex nature, diesel engine airpath has been an interesting plant for control research for decades. However, PID control with extensive gain scheduling structure is the most common in the industrial application softwares. Since sensors have inevitable delayed nature and fast tracking is crucial for engine performance and emissions, feedforward term plays an important role in the airpath control problem. A recent airpath feedforward control study is the dynamic feedforward control with predetermined optimum tables (Mancini *et al*., 2014). This study utilizes speed and fuel quantity based static feedforward maps and applies an optimized dynamical correction on them. Suggested implementation is explicit. Changes in the boundary conditions such as backpressure and inlet depression is not taken into the account and main problems of the static mapping are unresolved while its transients are improved.

Gaussian process regression (GPR) models are being used for online inverse modeling of the robotic systems (Schreiter *et al*., 2016). In an automotive application, inner loop dynamics of the throttle valve is represented by nonlinear autoregression with exogenous inputs (NARX) model whose nonlinear part is a GPR (Bischoff *et al*., 2013). Diesel engine fuel systems dynamics are modelled with local gaussian process regression in Tietze (2015) for offline model based calibration. Current generation of an ECU supplier has an advanced modeling unit in its ECU and online simulation of GPR models become practical for the automotive industry. This is a new capability for the powertrain control development and its application areas is expected to be broadening.

A calibratable and physical model free control approach is sought in our work. Singularity free and accurate inverse model for the airpath is known to be a hard problem; therefore a data driven inherently smooth modeling approach is favorable. On the other hand, mapping feedforward terms with respect to the physical states rather than operation points makes calibration procedure robust to the boundary condition variations such as backpressure. GPR can be seen as a gray-box modeling procedure since it is physically interpretable and contains prior information itself instead of a total abstraction. This nature of the model distinguishes from other modeling approaches from calibratability point of view. Authors initiated feasibility study for GPR EGR inverse model recently (Aran and Unel, 2016). However, it was only a modeling study and control aspects were not discussed. Current study includes VGT as well, and develops both a GPR based feedforward controller and a discrete time sliding mode feedback controller (Sabanovic *et al*., 2003). The controller is preferred since it does not require computation of equivalent control. All the modeling and control studies are realized on a modeling environment called Virtual Drive (VD). The Virtual Drive was developed and enhanced based on Unver *et al*. (2016) and became an inhouse vehicle and powertrain modeling software of Ford Otosan Powertrain Controls team.

The organization of the text is as follows: Diesel engine airptha control problem is stated in Section 2, and the Gaussian process regression feedforward controller ise developed in Section 3. Discerete time sliding mode feedback control is provided in Section 4. Both modeling and control simulations are givenh in Section 5. Finally, the paper is concluded with several remarks and possible future directions are indicated.

2. DIESEL ENGINE AIRPATH CONTROL PROBLEM

A basic diesel engine airpath model is based on ideal gas law, isentropic compressor work, conservation of mass and throttle equation for the layout given in Figure 1. An engine simulation model requires 12 states to capture dynamics of the whole engine system (Unver *et al*., 2016). However, airpath models for control can be constructed

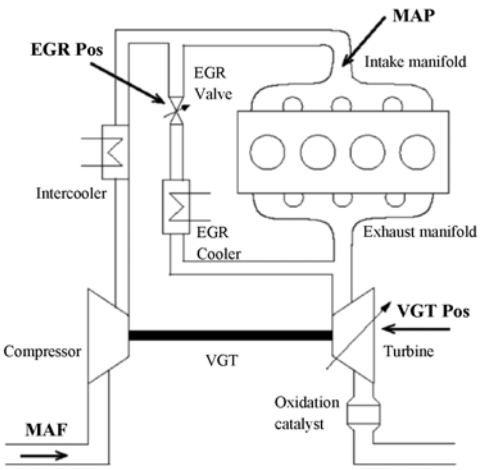

Figure 1. Airpath schematic of diesel engine (Jung *et al*., 2005).

with three states (Jankovic and Kolmanovsky, 1998; Jung *et al*., 2005) or one can include a fourth state if the throttle is included.

A widely used model for the intake manifold pressure P_i, exhaust manifold pressure P_x and compressor power P_c is given by (1) ~ (3) below. MAF, MAP, EGR position, VGT position and charge air cooler out gas temperature sensors are generally available in the modern serial production diesel engines.

$$\dot{P}_i = \frac{RT_i}{V_i}(W_{ci} + W_{xi} - W_{ie}) + \frac{\dot{T}_i}{T_e}P_i \tag{1}$$

$$\dot{P}_x = \frac{RT_x}{V_x}(W_{ie} + W_f - W_{xi} + W_{xt}) + \frac{\dot{T}_x}{T_x}P_i \tag{2}$$

$$\dot{P}_c = \frac{1}{\tau}(P_t - P_c) \tag{3}$$

Assuming constant temperatures (i.e., $\dot{T}_i$, $\dot{T}_x$ are zero) and following the steps in the literature (Jung *et al*., 2005), one can reach the control affine representation of the form

$$\dot{P}_i = f_1(P_i, P_c) + b_1(P_i, P_x)u_1 \tag{4}$$

$$\dot{P}_x = f_2(P_i, P_x) + b_2(P_i, P_x)u_1 + b_3(P_x)u_2 \tag{5}$$

$$\dot{P}_c = f_3(P_i, P_x, P_c) + b_4(P_x)u_2 \tag{6}$$

where u_1 and u_2 are control inputs which are EGR and VGT valve areas, respectively. If MAF (W_{ci}) is selected as one of the controlled outputs, then the output equation for the MAF can be written as

$$W_{ci} = \frac{P_c}{\eta_c c_{air}(\frac{P_i}{P_a})^{\mu}} \tag{7}$$

Equations (4) ~ (6) can be rewritten in control affine form as follows:

$$\dot{x} = f(x) + b(x)u \tag{8}$$

3. FEEDFORWARD CONTROLLER FOR THE AIRPATH

Engine development process gives the opportunity of operation region mapping. That means one can obtain nearly complete prior information of possible operation points and related inputs. These mappings are done for steady state operation points and also emission modeling design of experiments includes almost all feasible operation zone. If steady mappings, i.e. states for which $\frac{d}{dt}x = 0$, are available with complete state and controlled values, then the control effort required to conserve the measured states are known. Therefore, in light of (8), the feedforward control can be determined by setting $\dot{x} = 0$; i.e.

$$0 = f(x) + b(x)u_{ff} \Rightarrow u_{ff} = -{}^{f(x)}/_{b(x)} \tag{9}$$

Conventionally speed and inner torque based maps are used in the industry for the estimation of feedforward term. This study proposes a Gaussian Process Regression model based on physically related inputs such as P_x, P_i and W_{xi}.

Inverse actuator model for EGR (Wahlstrom and Eriksson, 2011) based on normal operation conditions is given by (10). In this equation Ar_{EGR} represents area of the EGR valve which is directly related to the EGR valve position (r_{EGR}), which is the output of the inverse actuator model. Obtaining desired accuracy for the EGR flow requires introduction of further parameters and their tuning in the aforementioned study.

$$Ar_{EGR} = \frac{W_{xi}\sqrt{RT_x}}{P_i\left[1 - \left(\dfrac{1 - \dfrac{P_i}{P_x}}{\Pi_{opt}} - 1\right)^2\right]} \tag{10}$$

Energy flow from turbine to compressor can be used for VGT inverse model. Total efficiency for VGT based on vane position can be defined as (11) using steady state turbine compressor energy balance.

$$\eta_T(r_{VGT}) = \frac{P_c}{W_{xt}h_{xt}(T_x)} \tag{11}$$

State Equation (3) can be rewritten in terms of efficiency as in (12).

$$\dot{P}_c = \frac{1}{\tau}(W_{xt}h_{xt}(T_x)\eta_T(r_{VGT}) - W_{ci}c_{air}(\tfrac{P_i}{P_a})^{\mu}) \tag{12}$$

As a result of presented physical modeling, input channels for the inverse EGR model are selected as P_i/P_x, P_i and W_{xi}. VGT inverse model inputs are W_{ci}, P_i, T_x, respectively, and its output is the VGT vane position (r_{VGT}).

3.1. Gaussian Process Regression for Diesel Engine Airpath

An engine operation point is defined with engine speed and torque. While engine speed is a result of created torque on the vehicle, the only control input to the engine is throttle pedal. Current commercial airpath controllers are mostly composed of an operation point table based feedforward and PID feedback controllers.

Operation point based table approach is not descriptive enough if the operation point does not fully describe the states of the system. In light of the physical model given in Section 2, it should be noted that the airpath behaviour is mostly determined by several physical parameters (states) other than speed and torque. Therefore, a model based feedforward that takes such states into account can handle the changes in the boundary conditions.

Interactions of the engine with the driver, environmental conditions and the vehicle create many possible test schemes that engine shall perform successfully. Control engineers fine tune the controller parameters based on test data to make sure that the vehicle satisfies customer requirements. In the light of this discussion, it is clear that a calibratable model is a necessity. Unlike a parametric model (simplified physical model or Neural Network), GPR embeds its training data into itself. Therefore, faulty training data points can be extracted and replaced by new ones very easily. GPR enables us with a multidimensional and statistically weighted interpolation hyper-table.

3.2. Gaussian Process Regression

It is assumed that the inverse actuator system is a zero mean Gaussian process model. A Gaussian process is a collection of random variables, any finite number of which has a joint Gaussian distribution (Rasmussen and Williams, 2006). The noise is assumed to be additive independent and identically distributed, and the ouput y is feedforward control value. The formulation detailed in Rasmussen and Williams (2006) will be followed in this section.

EGR and VGT channels are seperately modeled as multi-input (x: P_i/P_x, P_i, W_{xi} or W_{ci}, P_i, T_x) and single-output (y: r_{EGR} or r_{VGT}) (MISO) systems, respectively.

Prior covariance on the noisy output observations y_i and y_j is defined as

$$\mathrm{cov}(y_i, y_j) = k(x_i, x_j) + \sigma^2 \delta_{ij} \tag{13}$$

Covariance function $k(x_i, x_j)$ is defined over input samples x_i and x_j, and δ_{ij} is the Kronecker delta function. Definition of $k(x_i, x_j)$ for the squared exponential covariance term is given as

$$k(x_i, x_j) = \sigma_d e^{-0.5 r^T r} \tag{14}$$

where horizontal scale parameter σ_d is a scalar and r is a scaled input sample in terms of length scale parameters (l_j) which determine the weights between input channels.

For an experiment of m samples, one can construct the following covariance matrix that will be used in subsequent analysis:

$$K(X,X) = \begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \dots & k(x_1,x_m) \\ \vdots & \vdots & \vdots & \vdots \\ \dots & \dots & k(x_i,x_j) & \dots \\ \dots & \dots & \dots & k(x_m,x_m) \end{bmatrix} \tag{15}$$

Length scale "l" and horizontal scale "σ_d" are the main parameters of the model and they are called hyperparameters. These parameters are found by maximum likelihood estimation. Training values are used for finding hyperparameters and they are also embedded into the model through K matrix. The test values are the simulation inputs, current states in our case, whose outputs are calculated. Test inputs are denoted by x_*. The covariance vector between simulation point and the training points is represented as

$$k_* = \left[k(x_*, x_1) \quad k(x_*, x_2) \quad \dots \quad k(x_*, x_m)\right]^T \tag{16}$$

Predicted output y_* (u_{ffegr} or u_{ffvgt}) is calculated as

$$y_* = k_*^T (K + \sigma^2 I)^{-1} y \tag{17}$$

Parameter optimization procedure utilizes maximum likelihood cost function.

3.3. Modeling Details

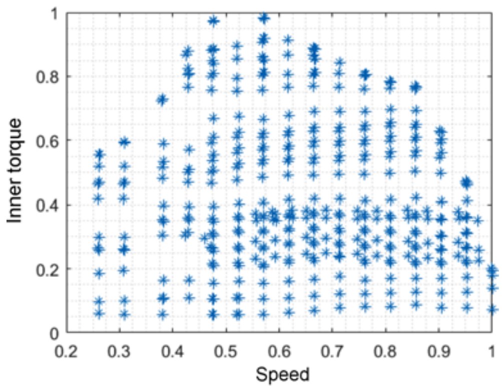

Figure 2. Engine mapping operation points.

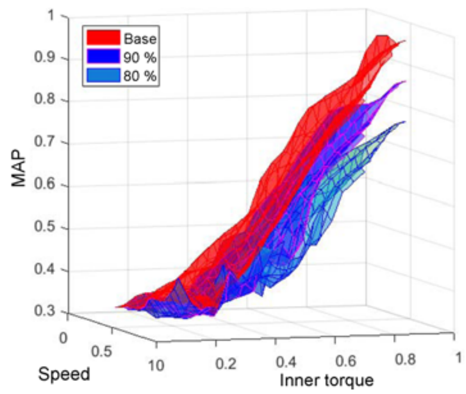

Figure 3. Three mapping boost values.

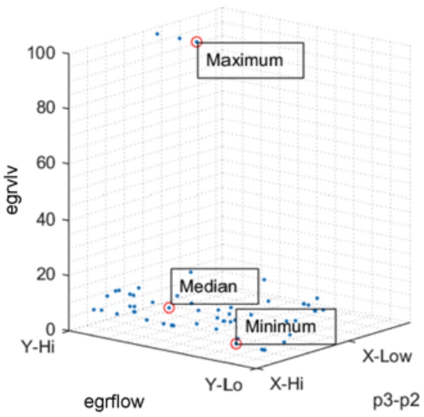

Figure 4. Sample training data selection bin.

Gaussian process regression requires a space filling design of experiment (DoE) for the inputs. Test data is collected with engine mapping simulations by setting speed and desired torque to grid points and waiting for 10 seconds settling, then averaging values of the last 30 seconds. Test grid of 417 points from the engine operation region is shown in Figure 2.

Boost delay is the characteristic of the turbocharger system, therefore mapping tests are repeated with 90 % and 80 % of the base calibration MAP values as shown in Figure 3.

Training points are selected with a bin logic. Input data is divided into bins of equal intervals and 3 values (i.e. minimum, maximum and median of the bin) from each bin is taken as training samples. A sample bin for EGR model is shown in Figure 4.

Training points are selected with the described logic and rest of the data are left for the validation. Total number of 179 training samples are selected for VGT and 1252 points are left for validation. EGR modeling required more training data (i.e. 312 samples for training and 1164 samples for validation) yet resulted in lower accuracy than the VGT inverse model. Model training is done with "fitrgp" function in MATLAB. Exact method is used with squared exponential kernel utilizing auto relevance determination in the form of (15) and (16). Hyperparameters l, σ_d, σ and α are extracted from "fitrgp" function.

4. DISCRETE TIME SLIDING MODE CONTROL

One of the aims of this paper is finding a flexible architecture in terms of related hardware's physical details. Although modelling of airpath is described in terms of simplified physical equations, this information is used only for input selection. Similarly extensive use of physical modelling is avoided in the feedback control as well. A discrete-time sliding mode controller developed by Sabanovic *et al*. (2003) is employed in this work. This controller does not require computations of equivalent control, and therefore detailed physical modelling is not

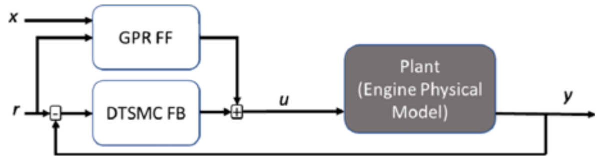

Figure 5. Overall control diagram.

necessary. For a control affine system as given in (4) ~ (6), a sliding surface can be defined as (18). The discrete-time sliding mode control law is given in (19). Controller sensitivity matrix B is the only plant related information.

$$\sigma = (\dot{x}_{\text{ref}} - \dot{x}) + C(\dot{x}_{\text{ref}} - \dot{x}) \tag{18}$$

$$u(t) = u(t-1) - (GB)^{-1}(\dot{\sigma}(t-1) + D\sigma(t-1)) \tag{19}$$

where D and C are design parameters and $G = \dfrac{\partial \sigma}{\partial x}$.

The whole control effort consists of GPR feedforward and sliding mode type feedback controller as depicted in Figure 5.

Simulation results are presented in the next section for MAF and MAP outputs.

5. RESULTS

Simulation model is a 13L heavy duty diesel engine model. WHTC (world harmonized test cycle) is the certification test cycle for dynamometer homologation of heavy duty diesel engines in Europe (UN ECE, 2013). Thus, WHTC is selected to asses controller performance. Normalized speed (n_norm) and torque (M_n) of this cycle are presented in Figure 6.

In the first set of simulations, we validated our feedforward GPR models for VGT and EGR at steady state operating conditions. Results for VGT and EGR valve position estimations are depicted in Figures 7 and 8, respectively. Although less training samples are used for VGT inverse model fitting (feedforward for MAP control), its validation accuracy is higher than EGR inverse model

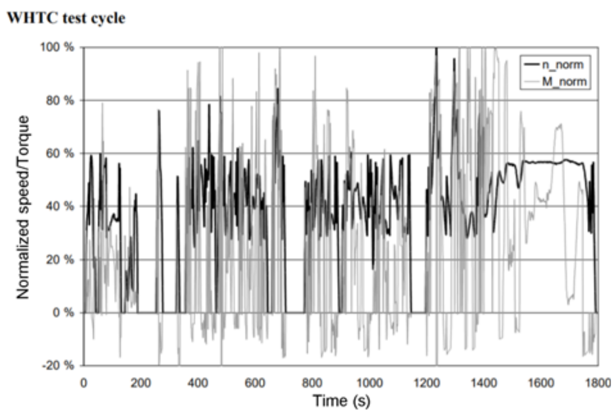

Figure 6. WHTC in speed (n_norm) and torque (M_norm) (UN ECE, 2013).

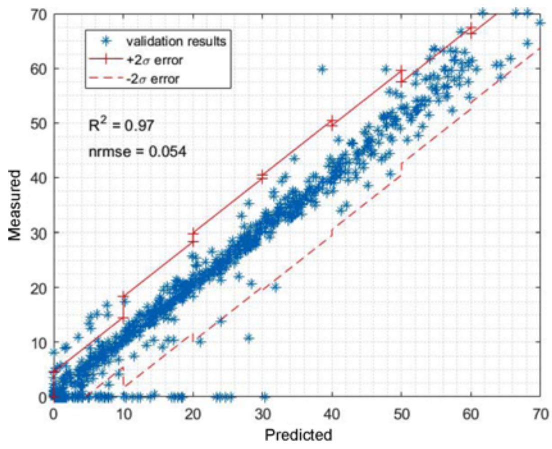

Figure 7. Validation fit results for VGT with 95 % validation confidence regions.

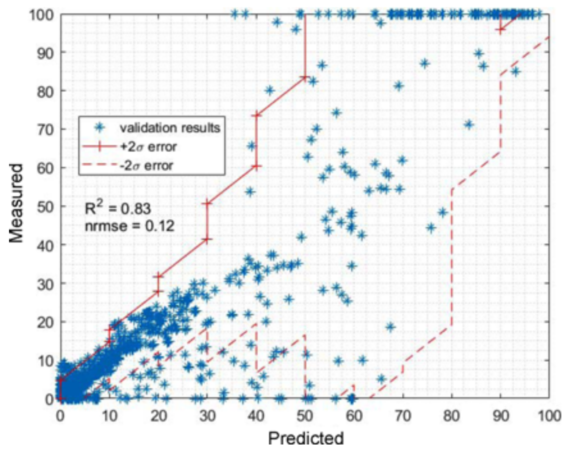

Figure 8. Validation fit results for EGR with 95 % validation confidence regions.

(feedforward for MAF control) as can be seen from the fit quality measures (e.g. R^2, nrmse, 2σ error bands) depicted on these figures.

Since our covariance function assumes smoothness on the EGR, the model accuracy is suffered from the singular behavior of the inverse plant when pressure difference is near zero as shown in Figure 9. Therefore, GPR with squared exponential kernel has been found not suitable for EGR feedforward modeling due to inherent discontinuity generated when pressure difference is close to zero.

The proposed SMC with GPR feedforward controller (SMC+GPR) is compared with a conventional controller (PID with table based feedforward for VGT) on WHTC cycle. Feedforward values for the conventional controller is directly taken from engine mapping data. Feedforward values are interpolated from tables which has engine speed and inner torque axes.

Performances of the controllers are checked on WHTC cycle where a 60 sec section corresponding to high torque gradients are illustrated. Due to inertial nature of the

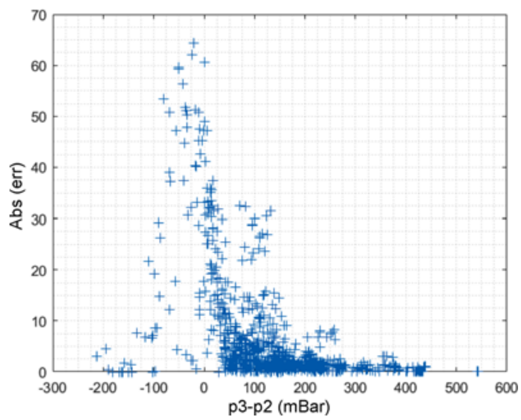

Figure 9. EGR model error vs Pressure difference on the EGR line.

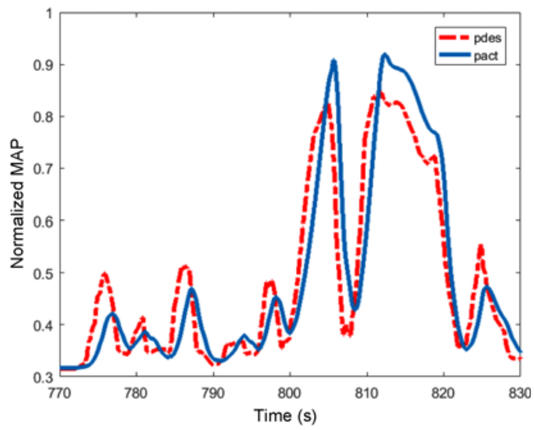

Figure 10. MAP tracking of conventional controller on a WHTC section.

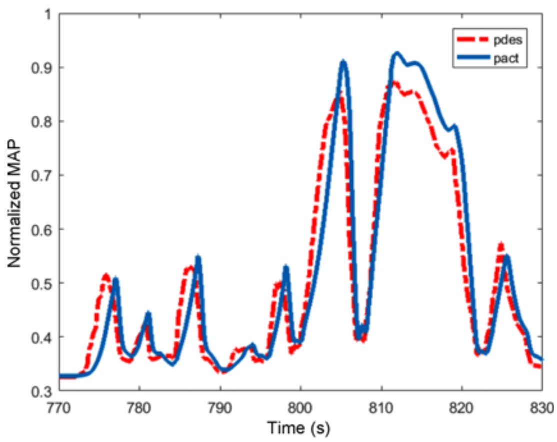

Figure 11. MAP tracking of SMC+GPR on a WHTC section.

turbocharger system, delayed behaviours are observed in the MAP tracking shown in Figures 10 and 11.

GPR based feedforward responded faster and more accurately to the sudden changes in the desired value as

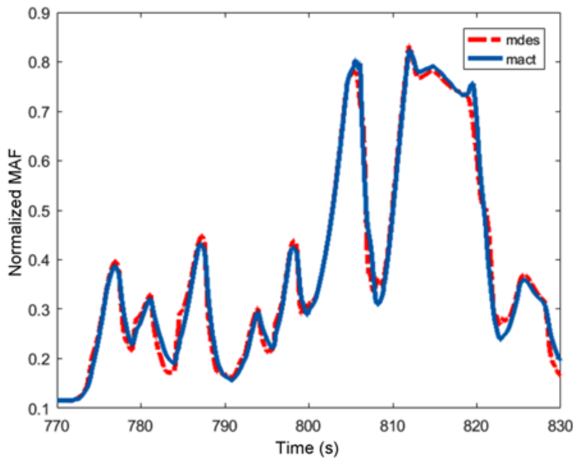

Figure 12. MAF tracking of conventional controller on a WHTC section.

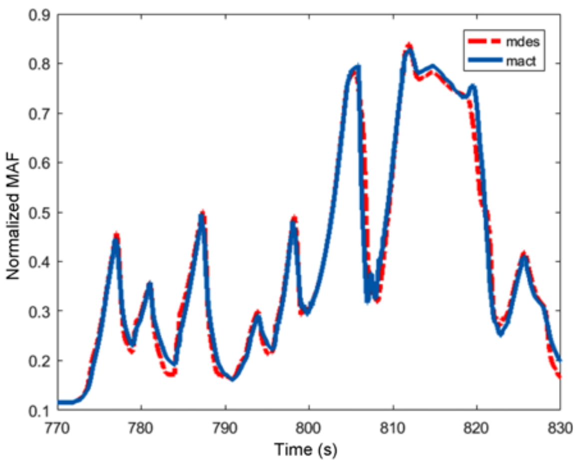

Figure 13. MAF tracking of SMC+GPR on a WHTC section.

seen at 810th second. Therefore, delays are minimized in Figure 11 when compared to Figure 10.

However, a properly tuned PID feedback controller performs similar to SMC controller for MAF as can be seen in Figures 12 and 13. Here it is hard to determine that if the tracking performance difference between SMC and PID is due to controller nature or MAP control interactions. It is known that smoother MAP control creates less

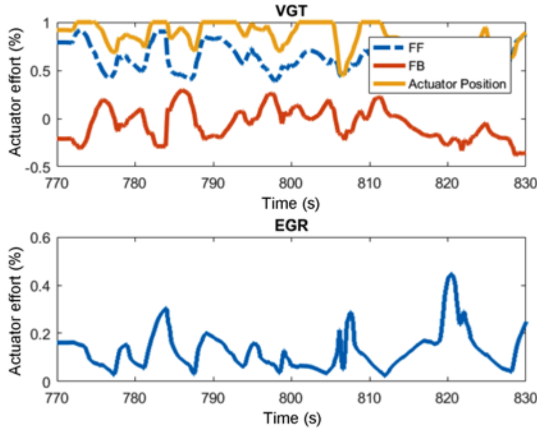

Figure 14. Actuator efforts of conventional controller on a WHTC section.

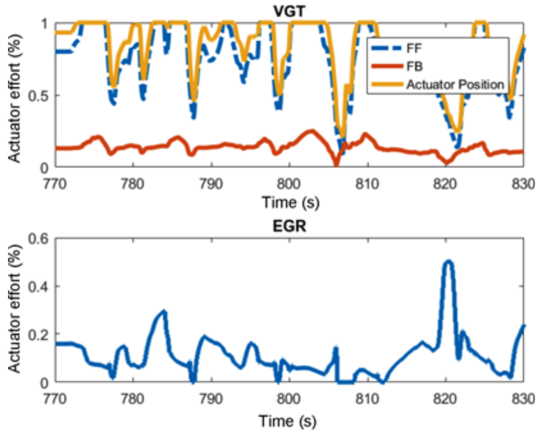

Figure 15. Actuator efforts of SMC+GPR on a WHTC section.

disturbance for the MAF, and therefore MAF control problem becomes easier.

Control efforts depicted in Figures 14 and 15 for the VGT channel show significant difference between the feedforward modeling approaches. This difference may be less obvious with quasi steady operation conditions. GPR model reduces the feedback control effort. EGR valve positions are similar in general but due to superiority of GPR feedforward in MAP control, less EGR control effort is required.

Table 1. WHTC performance metrics.

	MAF				MAP			
Method	bestfit	rmse	nrmse	R^2	bestfit	rmse	nrmse	R^2
PID+FF*	79,92	58,01	0,03	0,98	59,48	226,99	0,10	0,84
FB+FF* (SMC+GPR)	87,32	38,06	0,03	0,98	66,23	188,98	0,08	0,89

FB (SMC): Sliding mode feedback controller
FF (GPR): Gaussian process regression feedforward
FF*: Feedforward is used only for VGT.

Overall tracking performances of the implemented controllers with various metrics for the whole WHTC test cycle which ends in 1800 seconds are tabulated in Table 1 where bestfit results are expressed as percentages.

As can be seen from the table, MAF performance of conventional approach is poorer in terms of best fit metric but nrmse results are closer. This is due to existence of a few error peaks on the PID feedback controller through the cycle. This behavior is significant for soot production; therefore SMC+GPR controller is advantageous for airpath control. On the other hand, for the MAP control, the superiority of SMC+GPR is quite obvious in terms of all types of metrics.

6. CONCLUSION

We have now presented a new control scheme (SMC+GPR) which utilizes Gaussian process regression to estimate feedforward terms and sliding mode control as feedback controller to address the airpath control problem for diesel engines. Proposed GPR approach to feedforward modeling requires less data points than commercial table based approach. Feedforward modeling for VGT position using GPR achieves better tracking accuracy with less control effort and does not require any extra testing and tuning. Due to its discontinouity in certain operation conditions, EGR feedforward modeling is not successful with squared exponential kernel GPR. As a future study, improved GPR models for EGR will be investigated. Non-smooth nature of inverse EGR plant requires selection of specific covariance functions or finding another instrumental variable to alleviate the problem. Additionally, Manifold Gaussian Process (mGP) for Regression is suggested for improving GPR model for overcoming limitations (Calandra *et al*., 2014).

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REFERENCES

Aran, V. and Unel, M. (2016). Feedforward mapping for engine control. *Proc. IEEE Industrial Electronics Society, IECON Annual Conf*., 154–159.

Bischoff, B., Nguyen-Tuong, D., Koller, T., Markert, H. and Knoll, A. (2013). Learning throttle valve control using policy search. *Lecture Notes in Computer Science*, **8188**, 49–64.

Calandra, R., Peters, J., Rasmussen, C. E. and Deisenroth, M. P. (2014). Manifold gaussian processes for regression. arXiv: 1402.5876v4 [stat.ML].

Heywood, J. (2000). *Internal Combustion Engine Fundamentals*. McGraw-Hill. New York, USA.

Jankovic, M. and Kolmanovsky, I. (1998). Robust nonlinear controller for turbocharged diesel engines. *Proc. American Control Conf*., Philadelphia, Pennsylvania, USA.

Jung, M., Glover, K. and Christen, U. (2005). Comparison of uncertainty param- eterisations for H infinity robust control of turbocharged diesel engines. *Control Engineering Practice* **13**, **1**, 15−25.

Kolmanovsky, I. (1997). Issues in modelling and control of intake flow in variable geometry turbocharged engines. *Proc. 18th IFIP Conf. System Modeling and Optimization*, 436−445.

Mancini, G., Asprion, J., Cavina, N., Onder, C. and Guzzella, L. (2014). Dynamic feedforward control of a diesel engine based on optimal transient compensation maps. *Energies* **7**, **8**, 5400–5424.

Nieuwstadt, M. J., Kolmanovsky, I. V., Moraal, P. E., Stefanopoulou, A. and Jankovic, M. (2000). EGR-VGT control schemes: Experimental comparison for a high-speed diesel engine. *IEEE Control Systems* **20**, **3**, 63−79.

Rasmussen, C. E. and Williams, C. (2006). *Gaussian Processes for Machine Learning*. MIT Press. Cambridge, Massachusetts, USA.

Sabanovic, A., Sabanovic, N. and Jezernik, K. (2003). Sliding modes in sampled data systems. *Automatika: J. Control, Measurement, Electronics, Computing and Communications* **44**, **3-4**, 163−181.

Schreiter, J., Nguyen-Tuong, D. and Toussaint, M. (2016). Efficient sparsification for Gaussian process regression. *Neurocomputing*, **192**, 29−37.

Tietze, N. (2015). *Model-based Calibration of Engine Control Units Using Gaussian Process Regression*. Ph. D. Dissertation. Technical University Darmstadt. Darmstadt, Germany.

UN ECE (2013). E/ECE/324/Rev.1/Add.48/Rev.6-E/ECE/TRANS/505/Rev.1/Add.48/Rev.

Unver, B., Koyuncuoglu, Y., Gokasan, M. and Bogosyan, S. (2016). Modeling and validation of turbocharged diesel engine airpath and combustion systems. *Int. J. Automotive Technology* **17**, **1**, 13−34.

Wahlstrom, J. and Eriksson, L. (2011). Modelling diesel engines with a variable-geometry turbocharger and exhaust gas recirculation by optimization of model parameters for capturing non-linear system dynamics. *Proc. Institution of Mechanical Engineers, Part D: J. Automobile Engineering* **225**, **7**, 960−986.

Wahlstrom, J. and Eriksson, L. (2013). Output selection and its implications for MPC of EGR and VGT in diesel engines. *IEEE Trans. Control Systems Technology* **21**, **3**, 932−940.