Feedforward Mapping for Engine Control

Volkan ARAN
Faculty of Engineering and Natural Sciences
Sabanci University
&
FORD OTOSAN Product Development
Istanbul, Turkey
varan4@ford.com

Mustafa Unel
Faculty of Engineering and Natural Sciences
Sabanci University
Istanbul, Turkey
munel@sabanciuniv.edu

***Abstract*-Feedforward control is widely used in electronic control units of internal combustion engines besides feedback controls. However, almost all feedforward control values are used in table form, also called maps, having engine speed and engine torque in their axes. Table approach limits all interactions in two input dimensions. This paper focuses on application of Gaussian process modelling of errors of inverse parametric model of the valve position. Validation results based on real engine data are presented for steady and dynamic conditions.**

Keywords—Gaussian process regression; diesel engine air path; open loop control; engine mapping; EGR

I. INTRODUCTION

Increasingly stringent emission regulations of the diesel engines created the need for better engine out emission control. Diesel engine emission control can be examined under two titles: Air path and Fuel path. Air path control consists of mainly regulating following three actuators: throttle valve, exhaust gas recirculation valve, variable geometry turbine vane or waste gate. Transient control of diesel engine air path is focused on transient emissions and torque build up. One of the most important exhaust emission gases is Nitrous Oxide. Exhaust gas recirculation (EGR) system is the major NOx reduction system for engine out emissions [1]. Common controlled outputs of the diesel engine air path are the fresh airflow to the engine (MAF) and intake manifold pressure (MAP). This study focusses on control of MAF via EGR valve position. Regardless of type of the valve (poppet or butterfly) flow control with a valve is a non-linear control problem. Diesel engine air path has been a plant for nonlinear control research for decades. With the variations in the application PID control is one of the standard methods in the air path control literature ([2], [3], [4], [5], [6], [7], [8]) besides increasingly popular model predictive control ([9], [10], [11], [12], [13], [14], [15]). Other advanced control methods such as: Sliding mode control ([16], [17], [18], [19]) , H infinity control ([20]) LQG LTR([21]), Adaptive Control ([22]) and Lyapunov control methods ([23]) are also found in the air path control literature with lower frequency. Although a variety of control approaches can be found in the literature commercial diesel engine commercial controllers still uses feedforward control and basic PID's as well as inverse models for determining feedforward valve positions. Recent air path feedforward control studies are dynamic feedforward control with predetermined optimum tables ([24]) and adaptive feedforward with reset control ([25]).

Map or table structure in engine control algorithms uses engine speed and engine torque (or fuel quantity) as axes desired values since all the external demands to the engine are defined in terms of engine speed (indirectly vehicle speed) and engine torque (related to the driver throttle pedal position). Common practice is using same parameters for mapping of feedforward control values. However, modern engines have to adapt different operation modes and environmental conditions. Thus, the real feedforward control values are different for the same engine speed and torque values for different operation modes or environmental conditions. Additional maps for different operation modes and environmental conditions are solving this problem. Although this solution works in real life application, number of necessary parameters for the tables is growing and the related development effort is being tried to de reduced. In recent years, there is a growing interest in Gaussian Process modeling approaches. Inverse model with Gaussian process regression is especially praised for accuracy and smoothness [26].

Aim of this work is to use Gaussian process models for feedforward mapping of air path control actuators. There are parametric inverse models in commercial diesel engine control softwares. They have good performance for most of the engine operation points. However, certain errors at critical operation points may become unacceptable. Retuning of parametric inverse models without altering the whole behavior of the model is not possible. This causes repetition of the whole validation cycle. Gaussian process regression offers a good alternative for both map and corrections logic of commercial engine control unit structure and parametric model error corrections. Combined modeling of feedforward maps of the diesel engine air path actuators with both parametric and nonparametric models is the main contribution of this study.

Forward system identification of the EGR line is presented in the next section. Physical insights and system identification methods are shown. Later, inverse actuator position modeling with parametric and nonparametric models are introduced. Performances of both models are compared on steady state real engine for both training and validation tests. Finally transient characteristics of the steady state trained models are shared. Strong and weak points of combined modeling is discussed.

II. FORWARD SYSTEM IDENTIFICATION

A. EGR System

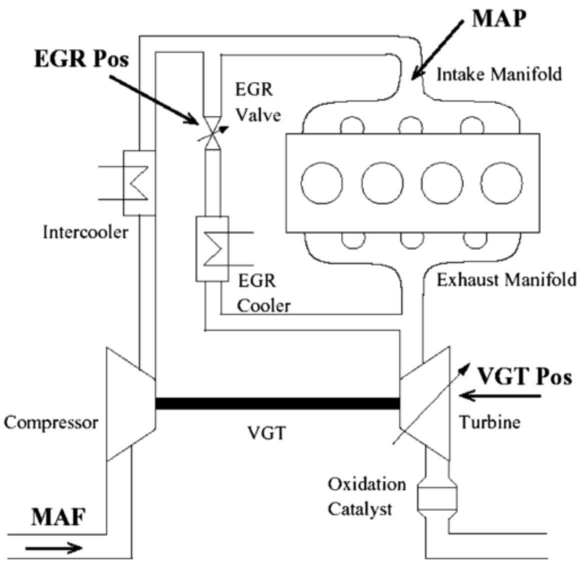

Fig. 1 Diesel Engine Air Path Scheme [20]

Exhaust gases from exhaust manifold are fed into the intake manifold for reduction of the engine out NOx emissions in modern diesel engines. This configuration is called high pressure EGR system (Fig. 1). Main driving force is the pressure difference between two ends of EGR line. Here forward system modeling is aimed to estimate the mass flow on the line based on the known pressure and temperature parameters.

In Diesel Engine Air Path Control literature EGR flow is modelled as compressible flow under variable restriction of the flow area. An example of simplified physical system model equation is presented in [27]. One-line compact version of the relation can be written as the following:

$$mass\ flow = \frac{Area\ P2\left[1-\left(\dfrac{1-\dfrac{P2}{P3}}{pi_{opt}}-1\right)^2\right]}{\sqrt{T3\,R_e}} \tag{1}$$

Where P2 is intake manifold pressure (or MAP), P3 is exhaust manifold pressure, T3 is exhaust manifold temperature, and R_e is gas constant, pi_{opt} is the model tuning parameter, which is added for low-pressure ratio along the line. Area is a function of actuator valve position and generally different from geometric area and tuned with test data. Positive flow is defined as flow from exhaust to intake direction and initially it is assumed positive only.

B. System Identification

Previous section presented nonlinear nature of the system. In order to facilitate transient data for the EGR flow model.

For the identification of the forward dynamic system, same tests with NOx identification method with novel chirp signals is used [28]. Model inputs are selected as P3, P2, T3, Total flow entering tot the engine (Fresh Airflow (MAF) + EGR flow) and modelled output is selected as MAF. The test designed to excite channels VNT position, EGR position, Engine Speed and Injection quantity with Chirp signals as described in [28]. Total flow through the engine is modelled as function of engine volume intake manifold pressure and temperature and volumetric efficiency of the engine.

Hammerstein model structure (No output nonlinearity) is selected for the identification of the system. MATLAB System Identification Toolbox [29] is used for creating the models. Regarding equation 1 polynomial nonlinearities of order 2 are selected for all input channels.

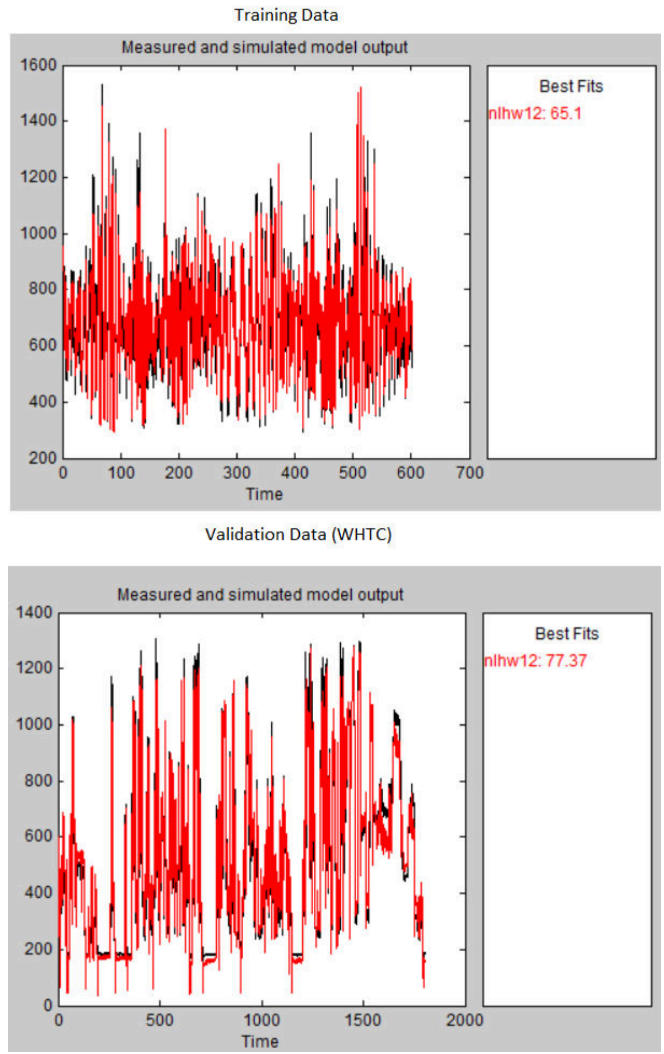

Fig. 2 Hammerstein Modeling Results on Training and Validation Data

As seen in Fig.2 validation results of MAF simulation on World Harmonized Test Cycle (WHTC) is promising, however higher accuracy in validation than accuracy of training reminds the lower complexity of validation test with respect to the training test.

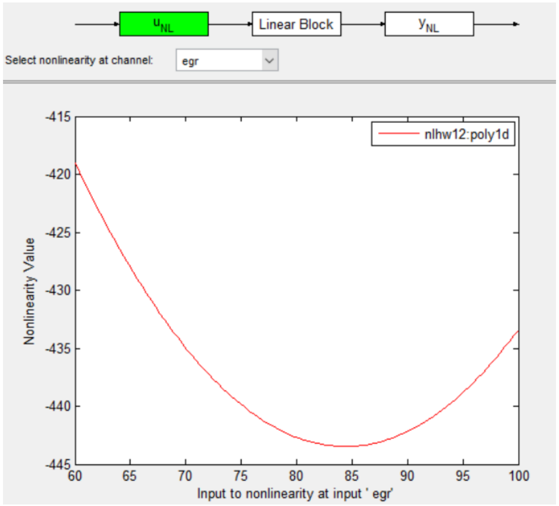

Fig. 3 EGR channel nonlinearity

Forward system can be modelled with certain accuracy but feedforward control requires inverse model of the system namely, model output of valve position with respect to other input parameters presented. However, with the same type of the model inverse model accuracies were very poor. One explanation for this result may be the non-invertible nature of the EGR nonlinearity found by forward model system identification. In Fig. 3 it is clearly seen that resultant system polynomial nonlinearity of EGR channel is not one to one.

III. INVERSE ACTUATOR POSITION MODEL

Here two modeling stage is being presented as in the Fig. 4. First, nonlinear inverse system is modelled with parametric model and output errors of the parametric model is covered with Gaussian Process Regression. (GPR). This approach is investigated on steady and transient data sets in following two subsections.

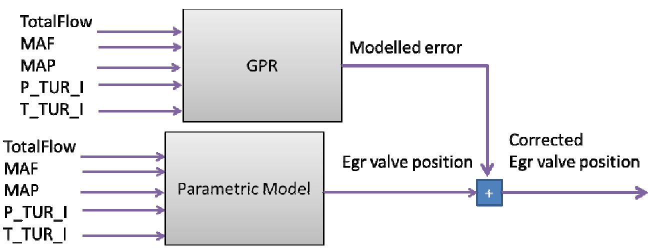

Fig. 4 Model Input - Output Scheme

A. Gaussian Process Regression for Parametric Model Error

Although Gaussian Process Model accuracy and ease of implementation are favorable, computational cost is high for commercial engine control units and it is the main drawback of the method for the industry. Regarding current commercial engine electronic control unit resources, a relatively simple model is developed while keeping the essential benefits of the Gaussian Process Regression (GPR).

Parametric models on engines are generally physics based empirical models as described in previous section. However, these models are generally valid under certain assumptions (In our example: no reverse flow). Obviously, real physical system is more complex than simplified parametric models and the real physical system models consists of differential equations that cannot be solved faster than real time inside the embedded controller. Although simplified parametric models can be tuned for certain training data and model accuracy values in terms of errors can be fair for test data average, it may be necessary to have better accuracy at certain operation conditions. Once model is tuned parametric models cannot be easily altered for better accuracy at this certain point while keeping same model performance for the rest. Retuning all the model may require repeated validation in the whole space and this may be very costly in terms of both time and money in an automotive new model development cycle. However, this correction of the parametric model functionality is natural for GPR and if distance parameters are tuned accordingly GPR does not change output values of the initial parametric model where its prior performance is already good.

Assuming that the parametric model is a deterministic mean function for Gaussian Process of the inverse model error. (Gaussian Process: *"A Gaussian process is a collection of random variables, any finite number of which has a joint Gaussian distribution."* [30]). Assume that the noise is additive independent and identically distributed, and y is the error of the parametric model. In the sequel, we will follow the formulation detailed in [30].

Let the functional relationship between inputs (x) and the output (y) be given as:

$$y = f(x) + \varepsilon \ , \ \varepsilon \approx N(0, \sigma_n^2) \tag{2}$$

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

$$\text{cov}(y_i, y_j) = k(x_i, x_j) + \sigma_n^2 \delta_{ij} \tag{3}$$

where $k(x_i, x_j)$ is a covariance function defined over input samples x_i and x_j, and δ_{ij} is the Kronecker delta function. $k(x_i, x_j)$ is defined as:

$$k(x_i, x_j) = \sigma_d e^{-0.5 x_{jl}^T x_{jl}} \tag{4}$$

where σ_d is the horizontal scale parameter and x_{jl} is a scaled input sample given by

$$x_{jl} = \begin{bmatrix} \frac{x_{j_1}}{l_1} & \frac{x_{j_2}}{l_2} & \dots & \frac{x_{j_n}}{l_n} \end{bmatrix}^T \tag{5}$$

where l_j is the length scale parameter.

Considering n samples of training inputs, one can construct the following covariance matrix that will be used in subsequent analysis:

$$K(X,X)=\begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \dots & k(x_1,x_n) \\ \vdots & \vdots & \vdots & \vdots \\ \dots & \dots & k(x_i,x_j) & \dots \\ \dots & \dots & \dots & k(x_n,x_n) \end{bmatrix} \quad (6)$$

Length scale "l" and horizontal scale "σ_d" are called hyper parameters. These parameters will be optimized for model training. In Gaussian process modeling there are two "x" values (so-called training and test values). Training values are used for finding hyper parameters and also they become part of the model itself. The test values are the simulation inputs whose outputs are calculated. Test inputs are denoted by x_*. The covariance vector between simulation point and the training points is defined as:

$$k_* = \left[k(x_*,x_1) \quad k(x_*,x_2) \quad \dots \quad k(x_*,x_n)\right]^T \quad (7)$$

Finally, the predictor equation is given as:

$$f_* = k_*^T (K+\sigma_n^2 I)^{-1} y \quad (8)$$

The cost function (log likelihood) for the Maximum Likelihood hyper parameter estimation is given as:

$$\log p(y\,|\,X) = -0.5 y^T \alpha - trace(\log(L)) - n/2 \log(2\pi) \quad (9)$$

where n is the number of training inputs and

$$\alpha = L^T (L \setminus y) \quad (10)$$
$$L = cholesky(K+\sigma_n^2 I) \quad (11)$$

Note that L is obtained through the Cholesky decomposition.

There are two challenges in Gaussian process modeling: Finding the hyper parameters and selecting the training points. In this work simple methods are carried out to overcome these two problems. First, hyper parameters are found by numerical optimization. Local minimums are found with gradient based optimization with MATLAB's *fmincon* function. This was possible because of the limited number of training points. (Remember training of the model needs inverse of the K matrix which is n by n). With increasing number of n, optimization time will be longer. Latter challenge is solved with selecting training points having error values of higher than certain threshold (see Fig. 5).

Parametric Model in Fig. 4 is selected as a second degree polynomial with 6 parameters:

$$EGR_{position} = c_1 EGR_{flow}^2 + c_2 (P3-P2)^2 + c_3 EGR_{flow}(P3-P2)\dots$$
$$+ c_4 EGR_{flow} + c_5 (P3-P2) + c_6 \quad (12)$$

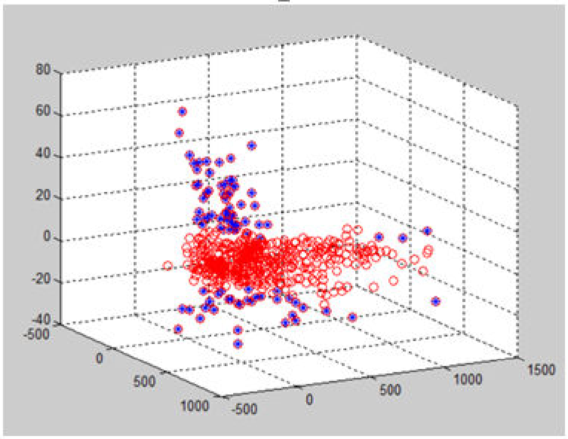

Fig. 5 Training data points selection

IV. SIMULATION RESULTS

Parametric model is fitted to steady state engine data of 524 points with R-square value of 0.72. For the training data, top 60 highest error points are selected. Maximum likelihood estimation is done via optimization of GPR hyper parameters. Combined model reached an R-square value of 0.91 (See Fig. 6). The aim of correcting the parametric model without making trade-offs from its general performance is achieved.

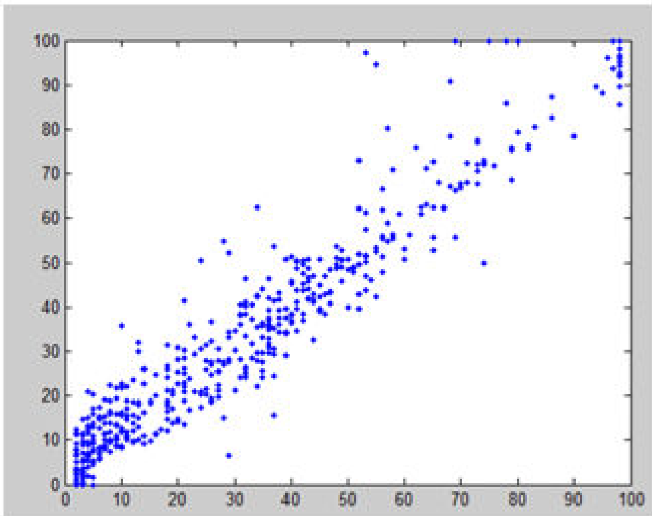

Fig. 6 Combined model results (x axis: measurement and y axis: model)

The aim of the study was finding better feedforward control values. Model is next validated on a transient engine cycle. First steady state engine operation points (engine speed and total injection quantity) of the engine are simulated with parametric model and R-square value of 0.55 is obtained. Error modeling with GPR raised the fit value to 0.98. In order to see transient generalization performance of the steady tuned inverse model, WHTC simulations are compared with measured valve positions. Here parametric model has fit value of 0.39 where combined model has 0.46 (Fig. 7). The gap between combined and parametric models became narrower as shown above. However, there are apparent accuracy increase especially steady sections of the test as seen in Fig. 8.

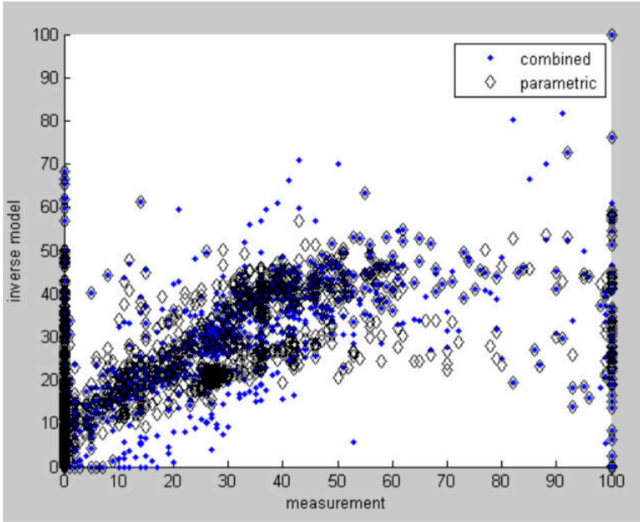

Fig. 7 Inverse model on transient cycle

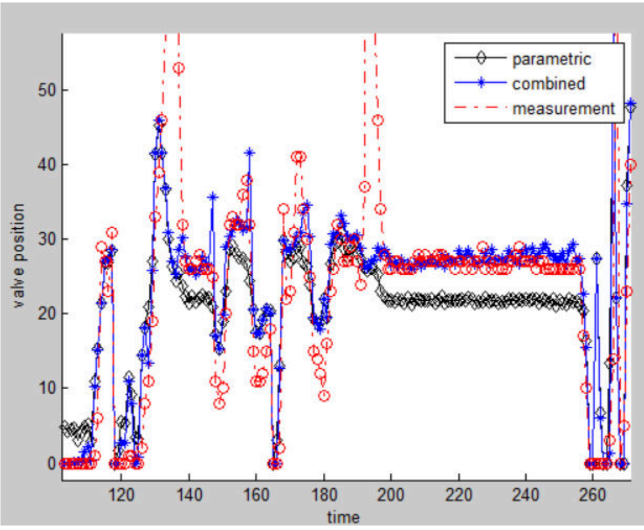

Fig. 8 Valve position vs. Time

V. CONCLUSION

Gaussian process error modeling is successful for improving model accuracy of the inverse valve position model without worsening the behaviour on the already accurate points. Since the number of training points is limited, fast simulation and training is possible while generalization performance on the transient test was limited.

For the better transient inverse modeling, adaptation of training points or using additional filtering may be necessary. In addition to the inverse model improvement, this type of models with feedback control will be considered as a future work.

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