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Diesel Engine NOx Emission Modeling with Airpath Input Channels

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***Abstract*—Stringent international regulations in terms of emissions necessitate more efficient transient calibration procedures for diesel engines which in turn implies utilization of dynamic models of the combustion process. In this paper, a novel input design framework in terms of multi-sweep chirp signals is developed and airpath input channels are excited by designed chirp signals. Linear and nonlinear system identification methods are utilized to model NOx emissions with airpath input channels. Experimental results show that while linear identification techniques provide poor performance in terms of training and validation fits, nonlinear models achieve remarkable performance in training and validation fits.**

I. Introduction

Diesel engines are widely used in both light-duty and high-duty automobile industry. Due to the hazardous emissions of diesel engines such as NOx gases and soot, governmental institutions regulates the maximum acceptable emission values which are exponentially declining. Therefore engine and vehicle manufacturers require a diesel engine combustion model to determine the best engine operating conditions that provides minimum emission values with maximum power. However combustion process in a diesel engine is a highly nonlinear dynamic system and physical modeling of this process is very challenging. Even a physical model is achieved, it will be only applicable for one specific diesel engine. As a consequence, a data-driven model is sought to optimize the parameters of the engine operating conditions.

Steady state modeling is used in the automotive industry where engine emissions are recorded for every possible input parameters. Then using these recordings, static maps are created as a function of selected input parameters and an optimization algorithm is run to estimate best parameters. This is a tedious and inefficient process and it does not take into account of the dynamic changes in the input parameters. With the introduction of very strict regulations that contain dynamic speed and load values, these steady state models do not give adequate results. Thus a transient (dynamic) modeling of diesel engine emissions is needed.

System identification is a very promising data-driven approach to model diesel emissions. There are various methods such as polynomial, block oriented and neural network type architectures [1], [2]. Early works utilized Volterra polynomials which have the ability to capture memory effects. It extends the convolution of the input signal with the system's impulse response to nonlinear terms of Volterra kernels and inputs [3]. Sakushima et al. use parametric polynomial Volterra series to model the diesel engine emissions and employ chirp signals with different frequencies and phases to the input channels [4]. However Volterra series have the disadvantage of having huge number of terms as the degree of the polynomial and number of inputs increase.

Due to the challenges of Volterra series, new block structure models are introduced [5]. Commonly used block structure models are Hammerstein and Wiener models which consist of a static nonlinearity block and a dynamic linear block. The Hammerstein-Wiener modeling structure was also used for identification of the SCR (selective catalytic reduction) system in diesel engines [6]. A priori knowledge about the system is used to choose the type of the nonlinearity blocks. Perez et al. used Hammerstein and Wiener models separately to model NOx emissions of a diesel engine [7]. Although they are successfully employed in many modeling efforts, they have hard time to model systems with highly nonlinear dynamics.

In addition to the classical approaches in nonlinear system identification, network structures, mainly neural networks and their derivatives are employed in the system identification [3]. The advantages of the neural networks are that they are conceptually simple; easy to train and use; have excellent approximation capabilities. System identification with neural networks are employed in diesel engine performance and emission modeling [8], [9]. Roy et al. used a feed-forward artificial neural network to model performance and emission of an engine [10]. The most significant disadvantage of neural networks is the overfit problem.

Nonlinear autoregressive moving average with exogenous inputs (NARMAX) model is introduced and developed to define and represent a broad class of nonlinear system identification methods [11]. Most of the model types explained above such as Volterra, Hammerstein, Wiener, multilayer neural network, and wavelet network can be seen as special cases of the NARMAX model [2]. The advantage of the NARMAX model is that it always seeks for a simple model structure with fewer terms. Recent works on system identification with NARMAX models show promising results and it is one of the most active research areas in nonlinear system identification. A polynomial NARMAX representation is used for relation between the variable geometry turbine command and the intake manifold air pressure [12]. Maass et al. utilized nonlinear autoregressive with exogenous inputs (NARX) model with a

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recurrent neural network to model the NOx emission of a heavy duty diesel engine [13].

In this paper, modeling of diesel engine NOx emissions is tackled within a novel input design framework for airpath channels. To this end, exhaust gas recirculation (EGR), variable geometry turbine (VGT), speed and fuel quantity channels are excited with chirp signals while rail pressure and fuel injection times and durations are kept at constant levels. More specifically, chirp signals with different frequency gradients are applied to the input channels to fill the space under the full load curve. While EGR and VGT channels are excited by one-sweep chirp signals with reversed frequency profiles. Similarly, speed and fuel quantity channels are driven by two-sweeps chirp signals with reversed frequency profiles. NOx emissions are modeled using both linear models including ARMAX and OE type model structures, and nonlinear models such as Hammerstein-Wiener and NARX with sigmoid network. Training and validation results show that linear models are incapable of capturing essential nonlinearities in airpath while nonlinear models provide satisfactory performance.

II. Diesel Engine

Diesel engine combustion can be divided into two main paths, namely air path and fuel path. In air path, first ambient air is sucked to the system with the help of a compressor and mixed with the recirculated exhaust gas. The amount of the ambient air is measured with a sensor and this value is recorded as Mass Air Flow (MAF). The amount of the recirculated exhaust gas is controlled with a valve called Exhaust Gas Recirculation (EGR). Mixed air is inserted into the combustion chamber through intake manifold. The pressure in the intake manifold is called Manifold Absolute Pressure (MAP). After the combustion, exhaust gases exit the combustion chamber through exhaust manifold. As it is said, a portion of the exhaust gas is provided back to the intake manifold via EGR. The remaining exhaust gases turns the turbine which is connected to the compressor. Therefore the velocity of the turbine determines the amount of ambient air sucked into the system. There is a valve called Variable Geometry Turbine (VGT) which adjusts the impact angle of the exhaust gases to the turbine blades.

Fuel is pumped into a common rail which has a specific pressure namely Rail Pressure. The fuel is then injected into the combustion chamber. The amount of injected fuel is controlled with an injector and the amount of fuel is called Quantity. The injection time is determined based on the crank angle that is called Start of Injection (SOI). A simplified structure of a diesel engine is given in Fig. 1.

III. Design of Experiments

Design of experiments consists of choice of model input signals, choice of experiment input signals, choice of excitation signals and choice of validation signals. In this paper, the effects of airpath input channels on the NOx emission of diesel engines are investigated. Chosen model input channels are shown in Fig. 2.

Although the NOx emissions model is constructed with mass airflow (MAF), manifold absolute pressure (MAP), speed and fuel quantity input channels, input signals of the experiments are different. In the experiments, EGR and VGT input channels are excited and resulting MAP and MAF values are measured. Chosen experiment input channels are shown in Fig. 3.

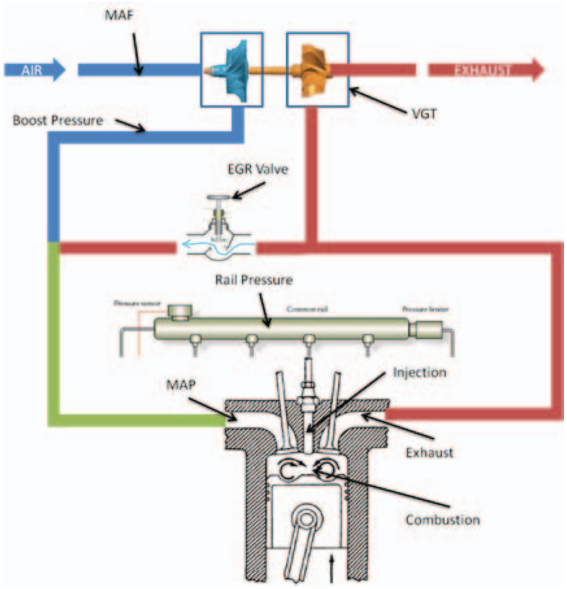

Fig. 1. Basic structure of a diesel engine

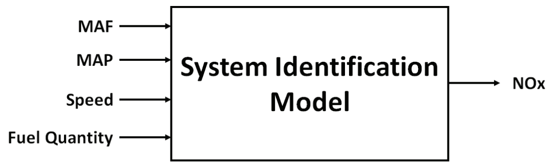

Fig. 2. Model input signals

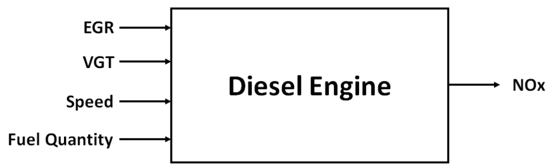

Fig. 3. Experiment input signals

Following the choice of experiment input signals, excitation signals were determined by investigating the World Harmonic Transient Cycle (WHTC) which is a world-wide homologation procedure applied to the diesel engine for regulation of exhaust emissions [14]. Normalized WHTC signal for load and speed is presented in Fig. 4.

The waveform of the excitation signals does not matter in system identification but signals' amplitude and frequency content is very crucial. As the periodic signals have advantageous in system identification framework [3], chirp signals were chosen as the excitation signals for the experiments. The other advantages of chirp signals are that they have lower crest factor that is shown in (1) and the amplitude modulation is easier compared to multi-sine signals [3].

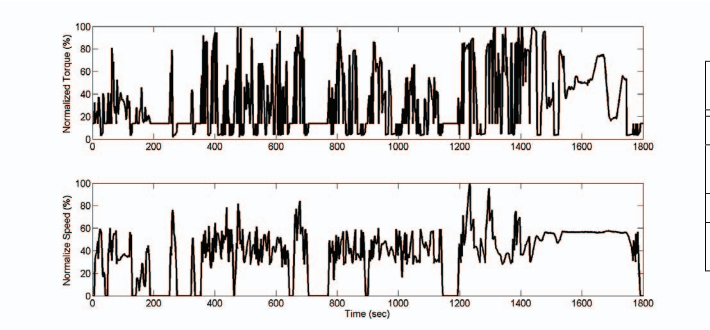

Fig. 4. Normalized WHTC speed and load reference

$$C_r^2 = \frac{max_t u^2(k)}{\lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{n} u^2(k)} \tag{1}$$

Chirp signals have the waveform of a sinusoidal signal but its frequency changes with time. The equation of a chirp signal is given in (2). The frequency of a chirp signal can change in a linear, quadratic or an exponential manner. Linearly changing frequency function is given in (3). The slope of the frequency is expressed in (4)

$$y = Asin(2\pi(f(t))) \tag{2}$$

$$f(t) = f_0 + kt \tag{3}$$

$$k = \frac{f_{max} - f_0}{T} \tag{4}$$

where f_0 is the initial frequency, f_{max} is the maximum frequency, T is the duration between f_0 and f_{max}, and k is the chirp ratio.

Following the determination of excitation signals, chirp signals with different frequency profiles were constructed to decrease the normalized zero-mean cross-correlation of input signals that is expressed in (5). Table I shows the calculated zero-mean normalized cross-correlation of excitation signals. Designed excitation signals are uncorrelated as the correlations between the signals are lower than 0.1.

$$\gamma = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \tag{5}$$

The initial and maximum frequency of the chirp signals were chosen by analyzing the Fast Fourier Transform of WHTC signal. Dominant frequencies are between 0.05Hz and 0.5Hz. Therefore, these values were chosen as the initial and maximum frequency.

Input channel chirp signals and their zoomed versions are depicted in Fig. 5 and 6, respectively. The frequency profiles

TABLE I. Zero-Mean Normalized Cross-Correlation of Excitation Signals

Signals	One-Sweep	Reversed One-Sweep	Two-Sweeps	Reversed Two-Sweeps
One-Sweep	1	0.0272	0.004	0.0015
Reversed One-Sweep	0.0272	1	0.002	0.0065
Two-Sweeps	0.004	0.002	1	0.0490
Reversed Two-Sweeps	0.0015	0.0065	0.0490	1

of the input channel chirp signals are displayed in Fig. 7. Measured MAF and MAP model input channels are presented in Fig. 8.

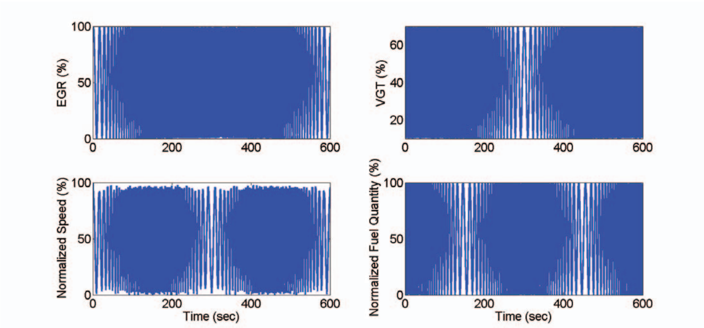

Fig. 5. Excitation signals of the input channels

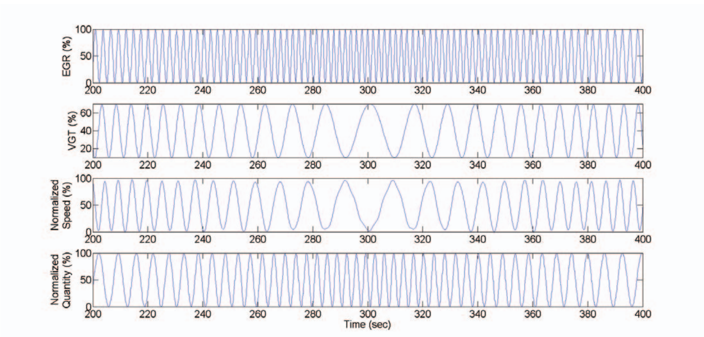

Fig. 6. Zoomed versions of excitation signals of the input channels

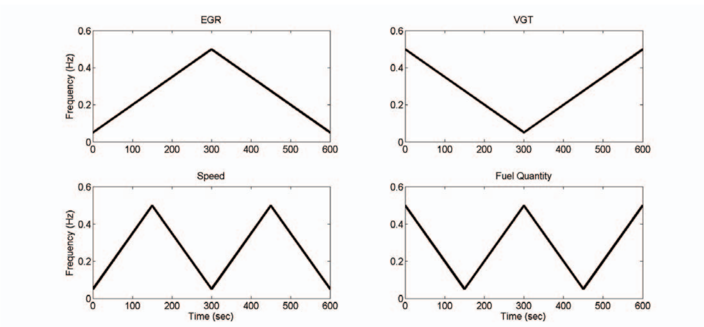

Fig. 7. Frequency profiles of experiment input channels

Additionally, validation experiments were carried out to obtain fresh data for the constructed models. Type of the

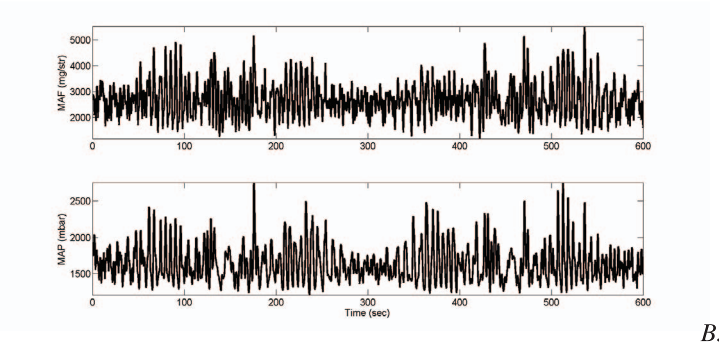

Fig. 8. Measured MAF and MAP input channels

validation input signals was chosen different than the type of the excitation signals. They were generated as ramp and hold signals.

IV. System Identification

A. Linear System Identification Models

Linear models are a special case of nonlinear models which hold superposition principle. A general linear model structure is shown in Fig. 9.

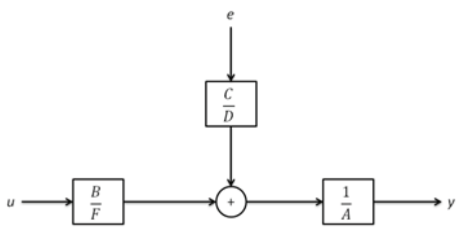

Fig. 9. General linear model structure

There are two main types of linear models. First one is equation error models where F and D polynomials are each 1 ($F = D = 1$). In these models noise goes through the same filter ($1/A$) as the input.

- *Autoregressive with Exogenous Variable (ARX) model:* In this model noise is considered as white noise, so C polynomial is simply 1 ($C = 1$). The parameters of this model can be found with linear regression. Therefore usually an ARX model is first fitted to the data and its parameters are used as parameter values for other models.
- *Autoregressive Moving Average with Exogenous Variable (ARMAX) model:* In this model, white noise (e) is passed through the filter C and a color noise is generated. In some cases, an integrator is applied to the noise to detrend the data. This integration effect acts like a first order difference for input and output signals. This model structure is called *ARIMAX*.

The second type of linear models are output error models where A polynomial is 1 ($A = 1$).

- *Output Error (OE) model:* In this model, white noise is directly added to the output. Hence C and D polynomials are each 1 ($C = D = 1$).
- *Box-Jenkins (BJ) model:* In this model, color noise is assumed to be added to the output. As in the ARMAX model, an integrator can be applied to the noise to detrend the data. This integration effect acts like a first order difference for input and output signals.

B. Nonlinear ARX Models

Nonlinear Autoregressive with Exogenous Variable (NARX) models represents a general form of the nonlinear system identification. The equation of a NARMAX model is given in (6).

$$y(k) = F[y(k-1), ..., y(k-n_a), u(k-d), ..., u(k-d-n_b)] + e(k) \quad (6)$$

Output depends on a nonlinear function of past values of inputs and output. The choice of the function F[.] defines the nonlinear system identification approach used in a problem. In this paper, the nonlinear function is chosen as a single-hidden layer neural network. The schematic of NARX with single-hidden layer neural network is given in Fig. 10.

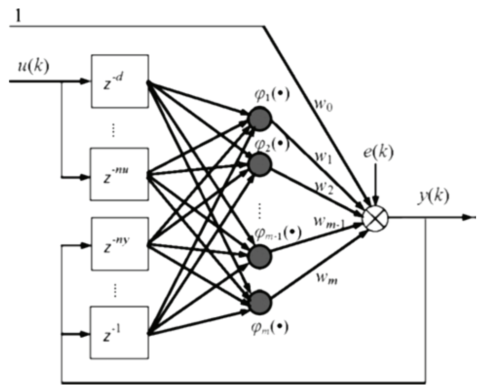

Fig. 10. A recurrent NARX network structure [1]

Mathematical expression of a recurrent NARX network structure is given in (7).

$$y(k) = F[x(k)] + e(k) = w_0 + \sum_{i=1}^{n} w_i \phi_i(x(k)) + e(k) \quad (7)$$

where w_i's are weights, *x(k)* is a vector of past values of inputs and outputs and $\phi_i(x(k))$ is a predefined activation function. The activation function used in this paper is Sigmoid function which is given in (8).

$$\phi(x) = \frac{1}{1 + e^{-ax}}, a > 0 \quad (8)$$

V. Results

A. NOx Modeling with Linear Models

First linear models were utilized to construct a NOx (ppm) emissions model. There is no preprocessing in the data. ARIMAX was selected from the equation error model structures and the numbers of coefficients in *A*, *B* and *C* polynomials are 5, 6 and 3, respectively. Box-Jenkins with integrator action was employed as the output error model and the numbers of coefficients in *B*, *C*, *D* and *F* polynomials are 4, 3, 4 and 5, respectively. The resulting training and validation fits of the linear models are shown in Fig. 11 and Fig. 12.

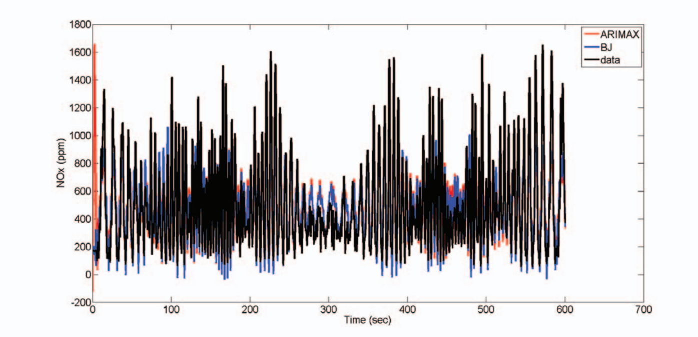

Fig. 11. Training results of linear NOx modeling

While the training accuracy of ARIMAX model is 42.42%, BJ model yields 51.13% training accuracy.

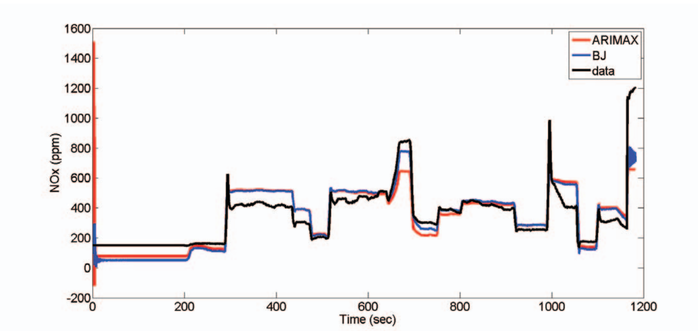

Fig. 12. Validation results of linear NOx modeling

ARIMAX model results in a 39.64% validation fit. The validation fit of BJ model is 51.02%. In order to increase training and validation fit results of linear models, means of the data are subtracted as a preprocessing method. In this case ARMAX and OE models are selected. The numbers of coefficients of *A*, *B* and *C* polynomials in ARMAX model are 2, 5 and 7, respectively. In OE model, the numbers of coefficients of *B* and *F* polynomials are 7 and 2, respectively. The resulting training and validation fits of the linear models with preprocessed data are shown in Fig. 13 and Fig. 14.

The training fit of ARMAX model is 51.81%. However there is a notable increase in the validation fit from 39.64% to 54.31%. In OE model, the training fit increased to 58.73% whereas the validation fit decreased to 47.77% compared to BJ model results.

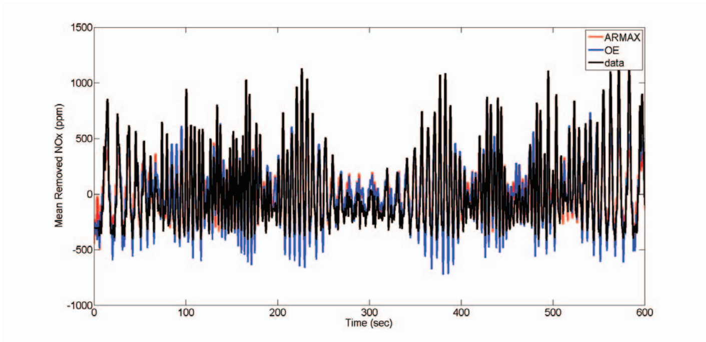

Fig. 13. Training results of linear NOx modeling with preprocessing

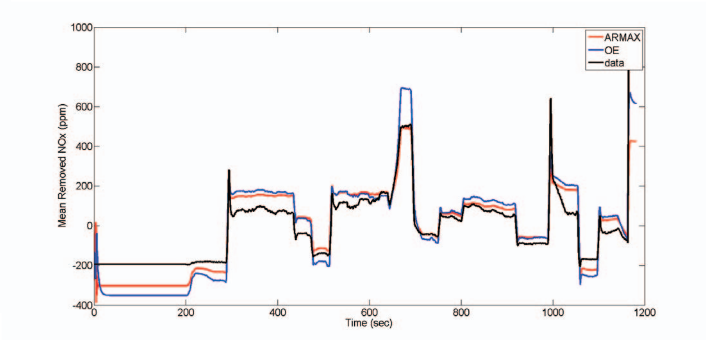

Fig. 14. Validation results of linear NOx modeling with preprocessing

B. NOx Modeling with Nonlinear Models

As the diesel engine combustion process is a nonlinear process, the performance of linear models is not satisfactory. Therefore a nonlinear model structure is utilized to model the NOx emission of the diesel engine. There is no preprocessing in the data.

Nonlinear model structure was Nonlinear ARX (NARX) with Sigmoid Networks. The model includes 5 previous values of each input channels and 1 previous value of output channel. The sigmoid network has 20 units. The resulting training and validation fits of the NARX wih sigmoid network model are shown in Fig. 15 and Fig. 16.

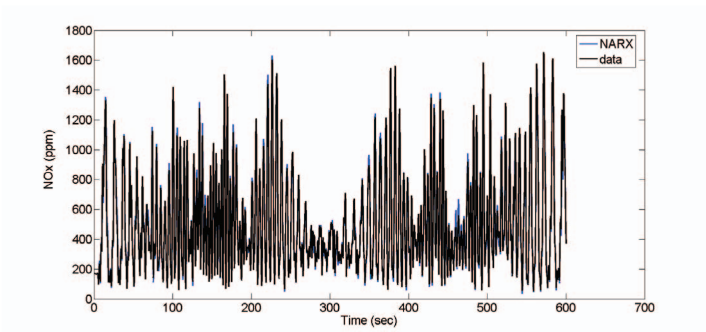

Fig. 15. Training result of NOx modeling with NARX

NARX model with Sigmoid Network produces a NOx emission model with 90.39% training fit. This is a very dramatic increase with respect to linear model results. Similar

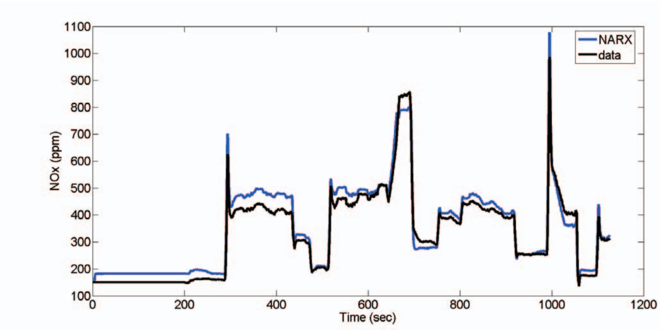

Fig. 16. Validation result of NOx modeling with NARX

to the training result of NARX model, there is a striking increase in the validation result which is 78.55%.

VI. Conclusion

A novel input design framework for diesel engine airpath channels is developed. Chirp signals with frequency profiles were designed and applied to the dynamic system. A validation signal was generated and applied to the system to obtain fresh data.

In linear models, highest training and validation fit values were achieved by using preprocessing tools (using noise integration and removing mean of the data). Linear models without preprocessing result in very low validation fit values. Removing the means causes loss in physical insight and it assumes that mean is known beforehand. However this is not guaranteed. On the other hand, nonlinear models increase the training fit of the models to 90% whereas validation fit of the models rises to 78%.

There are some input channels that we did not excite in the experiments, mainly rail pressure and start of injection. Incorporating the effects of these channels should result in a more comprehensive NOx emission model. Additionally, output torque, turbo inlet and outlet temperatures can be modeled with the same modeling approach.

Acknowledgment

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