SAE International

Developing a State Space Model for a Turbocharged Diesel Engine Using Least Square Method

2011-01-0758
Published
04/12/2011

Kamyar Nikzadfar and Amir Hossein Shamekhi
Khaje Nasir University of Technology

doi:10.4271/2011-01-0758

ABSTRACT

In this paper a state space representation of a turbocharged diesel engine is provided based on off-line least square method. Internal combustion engines show high nonlinear behavior due to complicated combustion phenomena and air flow dynamics inside the engine. In development phase of modern control methods like LQR controller, an accurate state space model with meaningful and measurable states is required. Identification is the method of deriving a mathematical model for dynamic systems based on input-output data. In this paper a mean value model of a turbocharged diesel engine is employed to generate demanded input-output data for identification purposes. This nonlinear mean value model predicts engine speed as a function mass of fuel injected per cycle, injection timing *(ξ)*, ambient pressure and temperature and external loads. In the next step the simulation data is used to develop a state space model around idle mode operation state. Least square method is then employed to identify a linear time invariant state space model out of input-output data. In doing so, band limited white noise is used to generate demanded I/O data for model identification purposes. In the next step subsequent results are used to identify the LTI model based on LS. Load is considered as a disturbance while mass of injected fuel and injection timing is two main inputs of the model. Engine speed is considered the only output. Inlet and exhaust manifolds pressure, turbocharger speed and engine speed are 4 states of engine. Comparison between the nonlinear model results and state space model data show acceptable similarity. The results show that this scheme can be used for online identification of engine in fault detection and adaptive control processes.

INTRODUCTION

Increasing demands for more efficient engines and stricter standard limits on exhaust gas pollutions require more accurate control on engine operating parameters. The first step in designing an appropriate controller is to develop an accurate yet simple to compute model. Engine behavior is nonlinear and nonlinear models are used to simulate its dynamic performance as well. Modern control methods such as State Vector Feedback Controllers (SVFC), Linear Quadratic Regulators (LQR) and Linear Quadratic Gaussians (LQG) request linear state space representation rather than nonlinear equations. Furthermore some parameters such as turbocharger (TC) speed and exhaust pressure are hard to measure and observers must be used to estimate the related states [1].

Many researches have been done to simulate and identify engine behavior for control purposes. A comprehensive review on different methods of nonlinear turbocharged diesel engine modeling is done by Kao and Moskwa [2]. They have classified different methods of engine modeling into two main categories of mean torque production and cylinder by cylinder modeling. In the former, the average of each parameter in about 10 successive cycles is used as model variables while in the former the instantaneous value of each parameter is used, each of which are suitable for a particular engine controller module. Governing physical equations as well as look-up tables are used to develop the nonlinear models. These models are developed based on thermodynamic and fluid dynamics phenomena equations.

On the other hand identification methods have also been used to identify a transfer function solely based on input-output data. Physical phenomena happening inside the engine are usually neglected in identification methods. Identification methods are categorized into two main classes of linear and

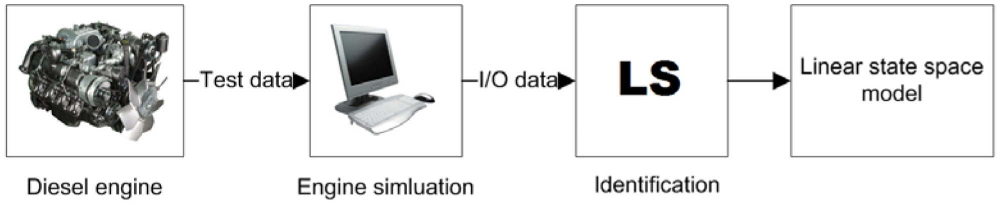

Fig. 1. Schematics of modeling and identification steps

nonlinear methods. Many nonlinear identification methods have been used to identify diesel engines with the purpose of engine controller design. Zito applied a polynomial NARMAX to identify a variable geometry turbine diesel engine based on input-output data [3]. Xiros used an uncertain Volterra representation to derive a dynamic model with respect to simulation results of a compression valve excitation [4]. Furthermore Salcado and et.al used Linear Parameter Varying (LPV) model to develop a nonlinear model for a diesel engine based on local linear models. Their model was able to predict engine behavior in a broad operating state. Also Karlsson and et al employed Wiener model and a clustering algorithm to model the engine dynamic based on identification of local linear models [5]. A new approach in identification of dynamic systems is employing dynamics artificial neural networks (DANN) in which feedback (dynamic) neural networks are trained to learn the behavior of dynamic systems. Ayoubial [6], Hafner [7] and Biao [8] employed DANN approach to simulate the steady and transient behaviors of diesel engines. On the other hand some linear identification methods have also been used to identify diesel engine. Jimboa and Hayakawab used the concept of role variables to transform the periodic state equation to a LTI state space equation [9].

Pseudo Random Binary Sequence (PRBS) is one the first successful methods used to obtain a discrete engine model transfer function. Local linearized continuous models which are derived from frequency domain identification methods or system perturbation are also the other methods which have been used to identify engine models [2].

In this paper the state space equation of a 1.6L turbocharged diesel engine is identified using State Space Parametric Model (SSPM). In doing so a mean value model (MVM) of the engine is developed first and the subsequent simulation data is used to indentify engine state space equation. Since the input/output data are simply result of modeling, the problem of noise and disturbances are avoided. The LTI state space equation can predict engine behavior in low speeds; it can also be used as a plant for developing idle speed controller. Schematics of research steps are illustrated in figure 1.

DIESEL ENGINE DYNAMIC MODELING

In order to identify the engine model a comprehensive model of engine is needed. The model should also be accurate enough to predict engine behavior under operational conditions. Many researches have been done to simulate the engine dynamic behavior. In order to simulate the dynamic performance of engine, MVM is utilized. To model the engine performance required information such as turbocharger maps, torque generation efficiency, geometric and dynamic characteristics of engine are collected from the test results obtained by Hendricks and et al. [10].

In modeling procedure, the steady state results and transient behavior data are used to calibrate and validate the model respectively. It should be noted that distinct operational condition are used for calibration and validation, however both procedures are done in low speeds as the model is supposed to be used for identification of engine in low speed range. The model contains inlet and exhaust manifolds, turbocharger, torque generation, internal friction and crank shaft dynamic sub models. Figure 2 illustrates the numbering sequence of engine. The variables in following equations are introduced in definition section of paper.

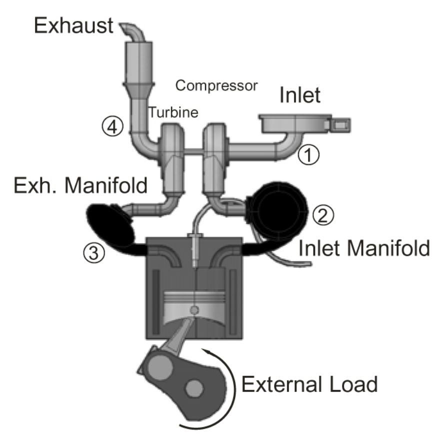

Fig. 2. Schematics of engine and numbering sequence

TURBOCHARGER MODEL

Turbocharger model comprises compressor, turbine and interconnecting shaft. There are different methods for modeling the dynamic performance of turbochargers. In this simulation a simple yet accurate model is used.

In order to compress the inlet air, mechanical energy is fed to compressor; the required mechanical torque is calculated using the following formula:

$$T_c = \frac{\dot{m}_c C_{pa} T_1}{\eta_c \omega_{tc}} \left[\left(\frac{P_2}{P_1} \right)^{\frac{\gamma - 1}{\gamma}} - 1 \right] \tag{1}$$

Compressor model is able to predict the required torque, flow rate and temperature of inlet air. The performance maps of compressor are usually published by turbocharger manufacturer and are used as a 2D lookup table in the following format:

$$\dot{m}_c = f_1 \left(N_c, \frac{P_2}{P_1} \right) \tag{2}$$

$$\eta_c = f_2 \left(N_c, \dot{m}_c \right) \tag{3}$$

These maps are applied in the model using the Hendricks and et al. test data [10]. The turbine generated torque is calculated as follows:

$$T_t = \frac{\dot{m}_t C_{p,e} T_3 \eta_t}{\omega_{tc}} \left[1 - \left(\frac{P_4}{P_3} \right)^{\frac{\gamma_e - 1}{\gamma_e}} \right] \tag{4}$$

Exhaust gas mass flow rate through the turbine is a function of turbine pressure ratio and turbine shaft speed. Also the turbine efficiency is a function of air flow Mach number and turbine shaft speed. These functions are similar to equations 2 and 3. These functions are also used in the model as 2D lookup tables.

Furthermore, the dynamic model of turbocharger shaft is used to interconnect the turbine sub model and compressor and is formulated using following equation:

$$T_t - T_c = I_{tc} \dot{\omega}_{tc} \tag{5}$$

Where I_{tc} is the rotational inertia of interconnecting shaft.

INLET AND EXHAUST MANIFOLDS MODELS

In turbocharged engines, the manifolds are intermediate volumes placed between compressor and inlet ports or turbine and exhaust ports. The air flow of turbine and compressor has been calculated before. The engine air flow rate is calculated using the volumetric efficiency as follows:

$$\dot{m}_{en}(t) = \rho_2(t) \eta_v \left(p_2, \omega_{en} \right) \frac{V_d}{N} \frac{\omega_e(t)}{2\pi} \tag{6}$$

It shows that volumetric efficiency is a function of inlet manifold pressure and engine RPM.

$$\eta_v = \eta_{v,p}(P_2) . \eta_{v,\omega}(\omega) \tag{7}$$

The results of a test are considered to investigate the effects of engine speed on volumetric efficiency [10]. The inlet manifold pressure plays an important role on volumetric efficiency; there are many models which predict the volumetric efficiency as a function of inlet pressure, in this research the following equation is used due to its high accuracy [11]:

$$\eta_{v,p}(P_2) = \frac{V_c + V_d}{V_d} - \left(\frac{P_4}{P_2} \right)^{1/k} . \frac{V_c}{V_d} \tag{8}$$

Inlet manifold pressure is calculated using the differential equation 9 which includes the compressor air flow rate and engine suction flow rate, already calculated in equations 2 and 6 [2]:

$$\dot{P}_2 + \frac{\eta_v V_d N}{120 V_{im}} P_2 = \dot{m}_c \frac{R T_2}{V_{im}} \tag{9}$$

Also temperature and pressure in formula 9 are calculated using following thermodynamic relations:

$$\dot{P}_3 = \frac{R_3 T_3 \left(\dot{m}_{ex} - \dot{m}_t \right)}{V_{em}} \tag{10}$$

$$T_3 = T_1 \left(\frac{P_3}{P_2} \right)^{\frac{\gamma_e - 1}{\gamma_e}} \left(1 + \frac{q_{in}}{c_v T_1 r_c^{\gamma_e - 1}} \right)^{\frac{1}{\gamma_e}} \tag{11}$$

TORQUE GENERATION, INTERNAL FRICTION AND CRANKSHAFT DYNAMIC MODELS

In order to model the engine accurately, the thermal efficiency of engine should be available. Engine torque generation depends on some of the engine operational parameters. It is shown that the diesel engine thermal efficiency is mainly a function of three major parameters:

$$\eta_{ind} = f(N, \lambda, \zeta) \quad , \quad \frac{1}{\lambda} = \phi = \frac{(F/A)_{actual}}{f_s} \tag{12}$$

The way which thermal efficiency is related to engine speed and equivalence ratio is derived using the experimental data. This function is applied into the model as a 2D lookup table. The effect of injection timing ζ on torque generation is modeled as a second order function [12].

$$\lambda_{\xi} = 1 - k_{\xi}\left(\xi - \xi_o(N, P_1)\right)^2 \tag{13}$$

In which $\xi_0(N, P_1)$ is the Maximum Brake Torque (MBT) conditions in every operational state. The result torque is calculated using energy equations. The generated torque, external load and internal friction torque together accelerate or decelerate the crankshaft. The following dynamic equation is used to calculate the engine speed.

$$T_{ind} - T_f - T_l = I_{cr}.\dot{\omega}_{cr} \tag{14}$$

In the above formula T_f represents the internal friction torque of engine moving parts and also pumping losses of engine. The pumping loss is calculated considering the difference between exhaust gas pressure and inlet pressure while the friction part is calculated as a function of both temperature and speed of engine [11].

$$bmep_{f,f} = k_1(T_{en}).\left(k_2 + k_3.S^2.\omega_e^{\,2}\right)\Pi_{e,max}.\sqrt{\frac{k_4}{B}} \tag{15}$$

In which the "k"s are fixed coefficient that are typical data for small diesel engines. "S" is engine speed and $\Pi_{e,max}$ is the maximum ratio of exhaust pressure to inlet pressure in low speeds. $k_1(T_{en})$ takes into account the temperature of engine while the other "k" factors are constant

MODEL VALIDATION

After calibrating of the model using steady state responses, it was tested by a step unloading of 10 N.m at 10th sec and subsequent loading of 10 N.m in 30th sec. Engine speed, inlet and exhaust manifolds pressures are employed to validate the engine simulation in figures 3, 4 and 5 respectively.

Also the manipulated variables are considered to validate the model; effects of both fuel injected mass and injection timing are verified by test data.

As figure 2 illustrates, the engine speed increases due to unloading in 10th sec and decreases to initial speed again. The trend of variations shows good similarity between experimental results and model ones.

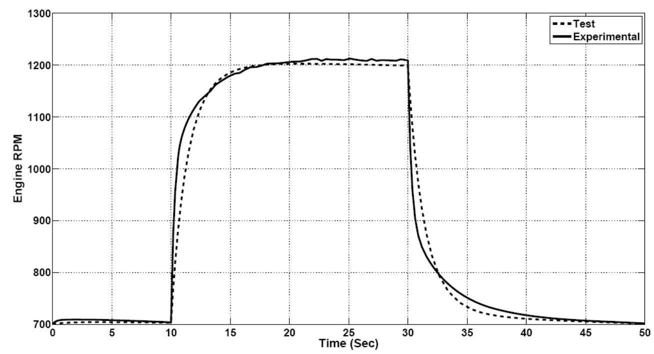

Fig. 3. Comparison of speed variation in model and experiment due to a step unloading and loading of 10 N.m

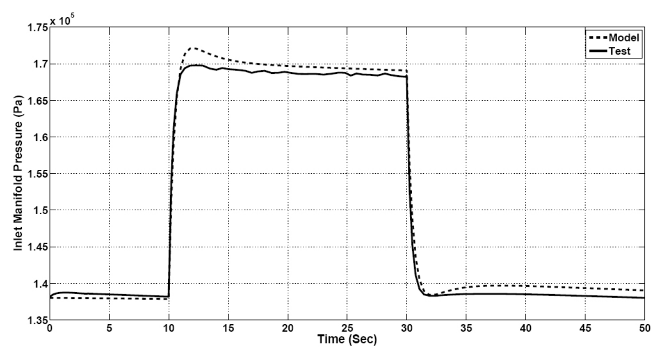

Fig. 4. Comparison of inlet man. pressure variations in model and experiment due to a step unloading and loading of 10 N.m

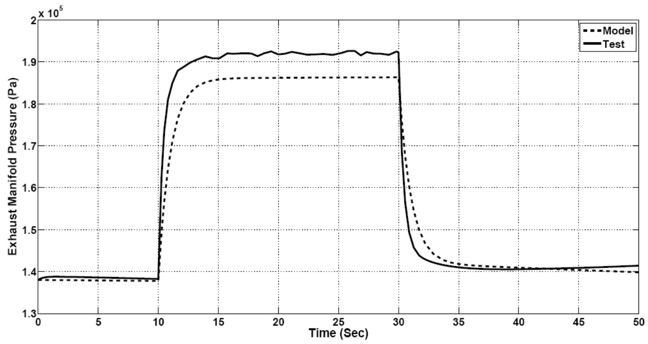

Fig. 5. Comparison of exhaust man. pressure variations in model and exp. due to a step unloading and loading of 10 N.m

A Steady State Error (SSE) is seen in both inlet and exhaust manifolds pressure. This SSE is because of simplifications in the estimation of gas temperature in manifolds. In order to increase the accuracy of estimation of temperatures, the convection heat transfer in manifolds should also be taken into account. Since this model is used in designing of engine controller, the model can be accepted owing to high robustness of controller in different ambient conditions and model parameters.

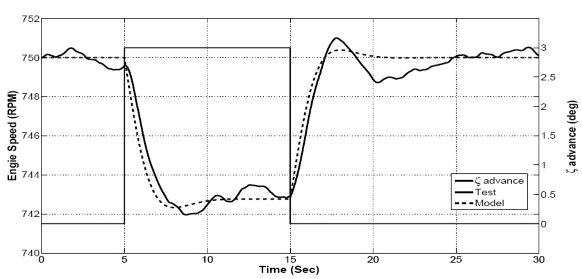

Fig. 6. Comparison of speed variation in model and experiment due to a step change in injection angle

An important manipulated variable is Injection timing ζ which will be discussed later. It will cause engine speed to vary. A test is done on the engine to see how the engine would response to ζ variation. In 5th second the injection angle is retarded 3 crank angles from MBT and is returned to MBT condition in 15th second. The low domain variations in speed are results of cycle by cycle variations in torque generation which are now more apparent. It also shows that the injection timing should be used to compensate for low speed disturbances.

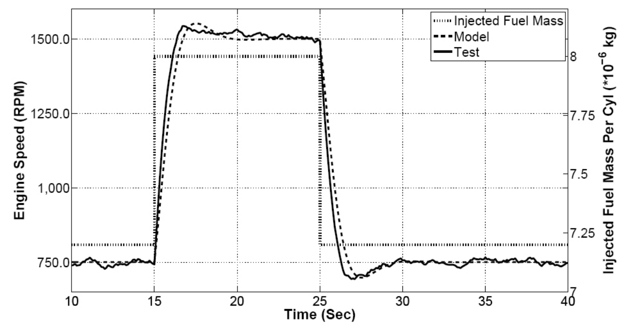

Fig. 7. Comparison of speed variation in model and experiment due to a step change in injected fuel mass

The other parameter which severely affects the engine speed is mass of fuel injected per cycle for every cylinder. The comparison between the model and experimental data show that model is able to predict the engine behavior accurately enough to be used as a plant for designing the controller.

DIESEL ENGINE IDENTIFICATION

OFF-LINE LEAST SQUARE METHOD

In this paper the off-line LS is used to estimate the dynamic and input matrices of the system. In LS method the I/O data are used to calculate the state space equation matrices. As discussed earlier in modeling section, turbocharged diesel engine has four main dynamics processes related to inlet manifold, exhaust manifold, turbocharger inertia and crackshaft inertia. The corresponding states are P_i, P_o, RPM_e and RPM_{tc} respectively. Therefore a system with 4 states is desired for simulation of the engine. Also 3 main inputs are considered, namely external load on the engine, mass of fuel injected to the cylinder and injection timing. The state and input vectors are as follow:

$$x = \begin{bmatrix} RPM_e & RPM_{TC} & P_i & P_o \end{bmatrix}^T \text{ and } u = \begin{bmatrix} L & m_{cy} & \xi_{inj} \end{bmatrix}^T$$

A state space equation is considered as follow with 4 states and 3 inputs:

$$x(k+1) = Ax(k) + Bu(k)$$

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \\ x_4(k+1) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \\ b_{41} & b_{42} & b_{43} \end{bmatrix} \begin{bmatrix} u_1(k) \\ u_2(k) \\ u_3(k) \end{bmatrix} \tag{16}$$

As seen in eq. 16, 26 distinct constants are to be calculated, 16 values for A matrix and 12 other constants for B matrix. In order to be able to calculate these 26 constants, the matrix is converted to following vector format to form the regression model:

$$[X_{I/O}(k+1)] = [A \quad B]\begin{bmatrix} X_{I/O}(k) \\ U_{I/O}(k) \end{bmatrix}$$
$$X_{k+1} = \theta_{4\times 7}.\phi(k)_{7\times 1} \tag{17}$$

In which the regressors matrix $\phi(k)$ is defined as follows:

$$\phi^T(k) = [x_1(k) \quad x_2(k) \quad x_3(k) \quad x_4(k) \quad u_1(k) \quad u_2(k) \quad u_3(k)] \tag{18}$$

And model parameter matrix is as follow:

$$\theta = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & b_{11} & b_{12} & b_{13} \\ a_{21} & a_{22} & a_{23} & a_{24} & b_{21} & b_{22} & b_{23} \\ a_{31} & a_{32} & a_{33} & a_{34} & b_{31} & b_{32} & b_{33} \\ a_{41} & a_{42} & a_{43} & a_{44} & b_{41} & b_{42} & b_{43} \end{bmatrix} \tag{18}$$

Also X_{k+1} is a vector corresponds to value of states in k+1. The θ matrix will then be calculated as follow:

$$\theta = X_{k+1}\phi^T\left(\phi^T\phi\right)^{-1} \tag{19}$$

The I/O data are fed to the LS algorithm to estimate A and B matrices. I/O data used in identification is generated from the MVM developed before. The generated data are selected so that they are able to take influences of all the inputs into account. Random white noise with appropriate intensity is used to generate the demanded data. In identification procedure, 7 distinct generated data sets are used simultaneously to model engine behavior accurately, some of which are illustrated in figures 8,9 and 10. The data used in identification are sampled in 0.1 sec intervals.

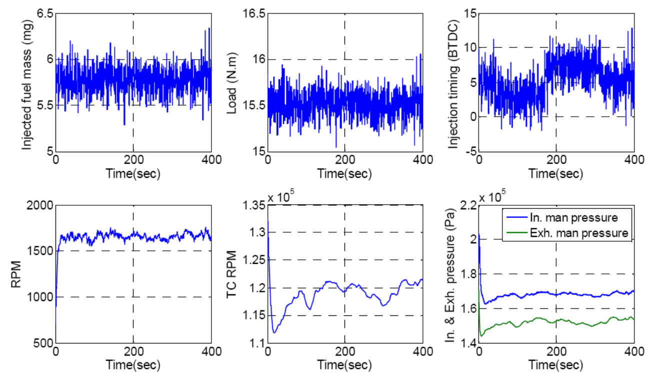

Fig. 8. A set of input-output data

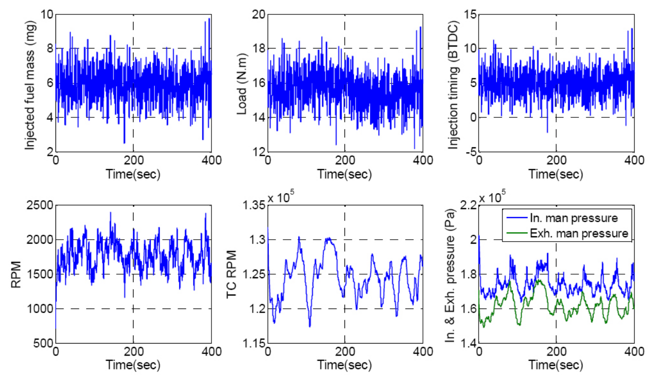

Fig. 9. A set of input-output data

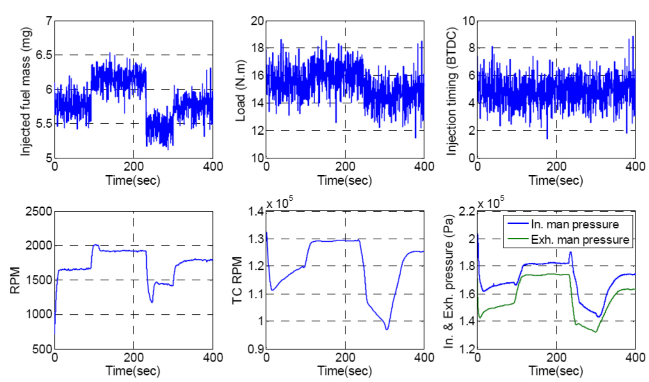

Fig. 10. A set of input-output data

In order to describe the engine state space in more meaningful manner, the input signals are expanded to disturbance signal and real input signals; load is really a disturbance while injected mass and injection timing are two real inputs to engine. So equation 16 will alter to following form:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) = Ax(k) + B_u u_{new}(t) + Ev(k) \\ rpm(k) = Cx(k) \end{cases} \tag{20}$$

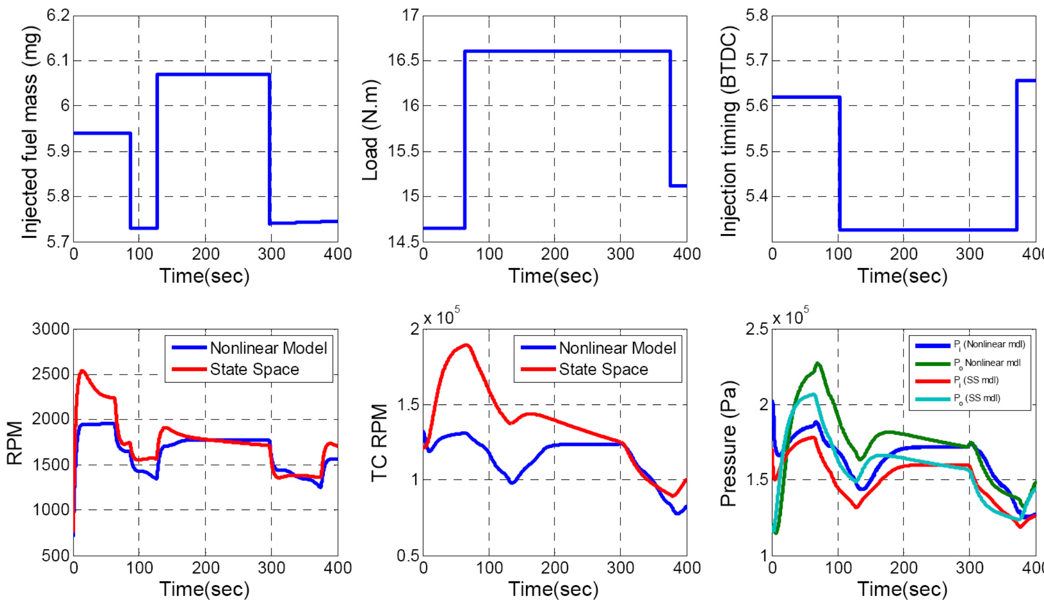

Fig. 11. Result of verification for pulse inputs

In which $v(k)$ is disturbance (load) and $u_{new}(k)$ is input vector which contains injection mass and injection timing. The matrices in equation 20 will calculated to be with $T = 0.1\ sec$

$$A=\begin{bmatrix} 0.9745 & 0.0003 & 0.2627 & -0.0002 \\ -0.1292 & 1.0001 & -0.0091 & 0.0111 \\ -0.2219 & -0.0012 & 0.9825 & 0.0243 \\ 0.6676 & -0.0006 & 0.0041 & 0.9900 \end{bmatrix}$$

$$B_u=\begin{bmatrix} 27.1113 & 0.2415 \\ -14.4390 & -0.0428 \\ -263.1368 & -4.4970 \\ -48.1888 & -1.7240 \end{bmatrix}, E=\begin{bmatrix} -6.5730 \\ 6.5211 \\ 80.2270 \\ 5.5196 \end{bmatrix}$$

$$C=\begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$$

Where A is state dynamic matrix, B_u is input matrix, E is disturbance matrix and C is output matrix.

STATE SPACE MODEL VALIDATION

The state space model is verified by appropriate stimulus, two test procedures are done to verify the state space model, one of them is solely sequences of step inputs and the other contains random signals. The results are illustrated in figure 11 and 12. The results show good agreement between state space and nonlinear models especially in engine RPM. The test results show that engine speed prediction has 19% error in the worst prediction situation due to initial value. The average error of engine speed is 5% in whole modeling period. On the other hand turbocharger speed and inlet and exhaust manifolds are respectively modeled with about 32%, 18% and 15% accuracy in their worst predication situation for random inputs. But the trends of variations show good agreement. The I/O data used in identification procedure influences the identification method. Since the speed is most important state to be predicted, the used data is selected in such a way to be able to identify engine speed well.

CONCLUSIONS

In this paper a procedure for identification of state space models for turbocharger diesel engines is investigated using subspace method. Since engine identification based on I/O data is a costly experimental procedure, mean value model of engine is utilized to generate I/O data instead. A 4th order state space model is identified based on generated data while effect of 3 inputs is taken into account. The order of state space system is selected based on main dynamic processes of engine. The generated data is shown to be an effective factor on performance of identification procedure. At last performance of identification is studied under different input variations; the results show that least square can model engine performance with good accuracy for engine speed and manifolds pressure; however the turbocharger speed has not been predicted with high accuracy which is due to nonlinearities. On the other hand trend of state space results are in good agreement with mean value model prediction for all the states. In conclusion the LS model can be used where engine speed and manifolds pressure prediction are important. In comparison to other methods of state space identification like subspace method, the accuracy decreases while the speed of identification increases. This method is best suitable for online identification due to its speed and lower calculations. It has also been shown that using a MVM model will decrease the cost of identification procedure, using this method will decrease the complexity of noise analysis and filtration which is a major problem in identification problems.

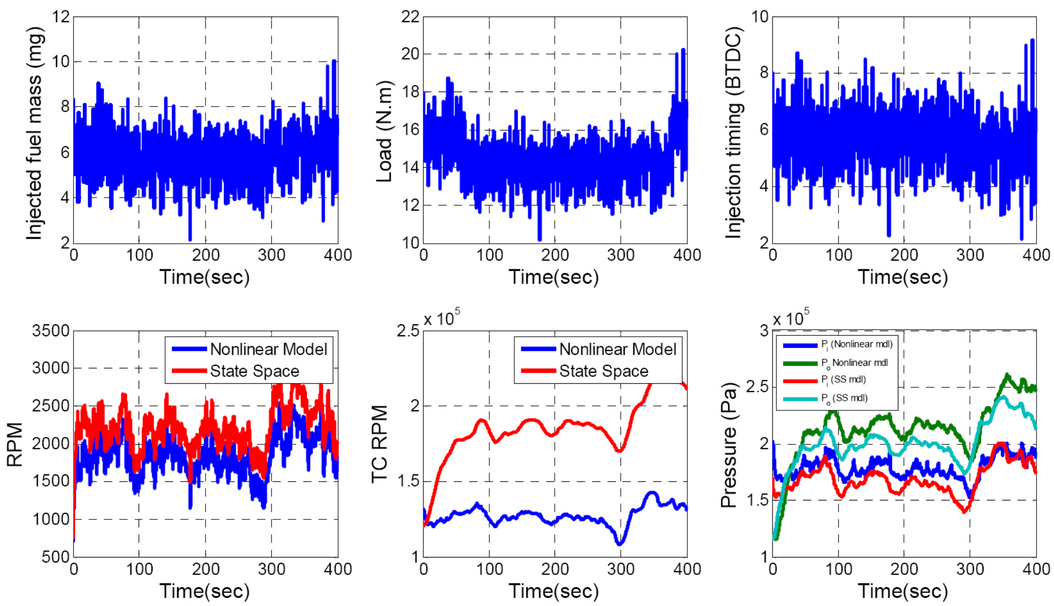

Fig. 12. Result of verification for random inputs

DEFINITIONS

Notation	Description	unit
B	Cylinder bore	m
$C_{p,a}$	Heat capacity of inlet air	$kJ/kg.K$
$C_{p,e}$	Heat capacity of exhaust gas	$kJ/kg.K$
$(F/A)_a$	Actual fuel to air ratio	
$fmep_f$	Friction mean effective pressure due to wet friction	Pa
f_s	Stochiometric fuel to air ratio	
I_{cr}	Crankshaft and engine rotating part inertia	$kg.m^2$
I_{tc}	Turbocharger shaft and blades rotational inertia	$kg.m^2$
$\dot{m}_c$	Mass rate of air through compressor	kg/sec
$\dot{m}_{en}$	The passing air mass flow rate through engine	kg/sec
$\dot{m}_{ex}$	Exhaust gas mass flow rate	kg/sec
m_f	Mass of injected fuel per cylinder	mg
$\dot{m}_t$	Mass rate of gas through turbine	kg/sec
N	Engine speed	RPM
N_{tc}	Turbocharger speed	RPM
P_1	Pressure of air before compressor	Pa
P_4	Pressure of exhaust gas after turbine	Pa
P_e	Exhaust manifold pressure	Pa
p_i	Inlet manifold pressure	Pa
q_{in}	Combustion specific heat value	kJ/kg
r_c	Compression ratio	
S	Piston stroke	m
T_1	Temperature of air before compressor	K
T_4	Temperature of exhaust gas after turbine	K

T_c	Compressor demanded torque	*N.m*
T_f	Friction torque	*N.m*
T_{ind}	Engine indicated torque	*N.m*
T_l	Load torque	*N.m*
T_t	Turbine generated torque	*N.m*
V_c	Combustion chamber volume	m^3
V_d	Engine displacement volume	
V_{im}	Inlet manifold volume	m^3

Notation	**Description**	**unit**
Γ_d	Observabilty matrix	
$\Pi_{e,max}$	Maximum ratio of exhaust pressure to inlet	
ϕ	Fuel to air equivalence ratio	
γ_a	Air specific heat ratio	
γ_e	Exhaust gas specific heat ratio	
η_c	Compressor efficiency	
η_{ind}	Engine indicated efficiency	
η_t	Turbine efficiency	
η_v	Volumetric efficiency of engine	
$\eta_{v,\omega}$	Volumetric efficiency (speed related part)	
$\eta_{v,p}$	Volumetric efficiency (Inlet manifold pressure related part)	
λ	Air to fuel equivalence ratio	
ω_e	Engine speed	*Rad/sec*
ω_{tc}	Turbocharger speed	*Rad/sec*
ξ	Injection timing	*BTDC°*
ξ_0	Injection timing correspond to MBT	*BTDC°*

ABBREVIATIONS

DANN
Dynamic Artificial Neural Network

I/O
Input-Output

LPV
Linear Parameter Varying

LQG
Linear Quadratic Gaussians

LQR
Linear Quadratic Regulators

LS
Least Square

LTI
Linear Time Invariant

MBT
Maximum Brake Torque

MVM
Mean Value Model

NARMAX
Nonlinear Auto-Regressive Moving Average with eXogenius inputs

PRBS
Pseudo Random Binary Sequence

SSPM
State Space Parametric Modeling

SVD
Singular Value Decomposition

SVFC
State Vector Feedback Control

TC
TurboCharger

VGT
Variable Geometry Turbine

REFERENCES

1. Ye, Zhengmao, "Modeling, Identification, Design and Implementation of Nonlinear Automotive Idle Speed Control Systems-An Overview", IEEE Transactions on Systems, Man and Cybernetics, November 2007

2. J Kao, M.H., Moskwa, J.J., "Turbocharged Diesel Engine Modeling for Nonlinear Engine Control and State Estimation" ASME Journal of Dynamic Systems Measurement and Control, Vol 117, March 1995.

3. Zito, G., Landau, I.D. "Narmax model identification of a variable geometry turbocharged diesel engine", American Control Conference, 2005

4. Xiros, Nikolaos I., Theotokatos, Gerassimos P., "Nonlinear Identification of a Turbocharged Diesel Engine Compression System Dynamics by an Uncertain Volterra Representation", ASME 2006 International Mechanical Engineering Congress and Exposition, 2006

5. Karlsson, Maria, Ekholm, Kent, Strandh, Petter, Johansson, Rolf, Tunestål, Per, "Dynamic mapping of diesel engine through system identification",: American Control Conference, 2010

6. Ayoubial, M., "Comparison between the dynamic multi-layered perceptron and the generalized Hammerstein model for experimental identification of the loading process in diesel engines", Control Engineering Practice, Volume 6, Issue 2, 1998

7. Hafner, M., Schüler, M., Nelles, O. and Isermann, R., "Fast neural networks for diesel engine control design" Control Engineering Practice, Volume 8, Issue 11, 2000

8. Biao, Liu Qing-chun, Lu Zhen-hua, Jin Sheng-fang, Nie, "System identification of locomotive diesel engines with autoregressive neural network" 4th IEEE Conference on Industrial Electronics and Applications, 2009

9. Jimboa, Tomohiko, Hayakawab, Yoshikazu, "A physical model for engine control design via role state variables", Control Engineering Practice, 2010

10. Jensen, J., Kristensen, A., Sorenson, S., Houbak, N. et al., "Mean Value Modeling of a Small Turbocharged Diesel Engine," SAE Technical Paper 910070, 1991, doi: 10.4271/910070.

11. Guzzella, L., Onder, C.H, "Introduction to Modeling and Control of ICE systems" Springer, 2004

12. Gerhardt, J., Hönninger, H., and Bischof, H., "A New Approach to Functional and Software Structure for Engine Management Systems - BOSCH ME7," SAE Technical Paper 980801, 1998, doi: 10.4271/980801.

The Engineering Meetings Board has approved this paper for publication. It has successfully completed SAE's peer review process under the supervision of the session organizer. This process requires a minimum of three (3) reviews by industry experts.

ISSN 0148-7191

SAE Customer Service:
Tel: 877-606-7323 (inside USA and Canada)
Tel: 724-776-4970 (outside USA)
Fax: 724-776-0790
Email: CustomerService@sae.org
SAE Web Address: http://www.sae.org
Printed in USA

SAE International