

# Nonlinear Oxygen Sensor Output Voltage Estimation in a Gasoline Engine Using NARX Model

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## Abstract

Great effect of three way catalytic convertor (TWC) performance on oxygen sensor output voltage has made the sensor (located after catalyst) as the main signal in almost all today's TWC monitoring algorithms. In this paper output voltage of nonlinear oxygen sensor is estimated using a nonlinear autoregressive with exogenous inputs (NARX) model. The estimation uses ECU calculated exhaust gas flow and air fuel ratio from upstream lambda sensor and does not need any unconventional sensor measurement. Combined with simple structure applied to the NARX model, an algorithm applicable to real-time computations on vehicle is designed. Estimated voltage is compared to real measurement from a car during new European driving cycle (NEDC), showing good performance of the estimation algorithm. Moreover, by tests results it is shown that this model can monitor the effect of catalysts aging

**Keywords:** *Three Way Catalytic Converter-Lambda Sensor- Model Based Monitoring- NARX Model*

## 1-Introduction

Importance of harmful emissions from road vehicles has become a major concern as their number has increased significantly during recent years. This increase of vehicles is reported to be more than ten fold over five previous decades which has caused 34% of produced oil to be consumed by vehicles [1].

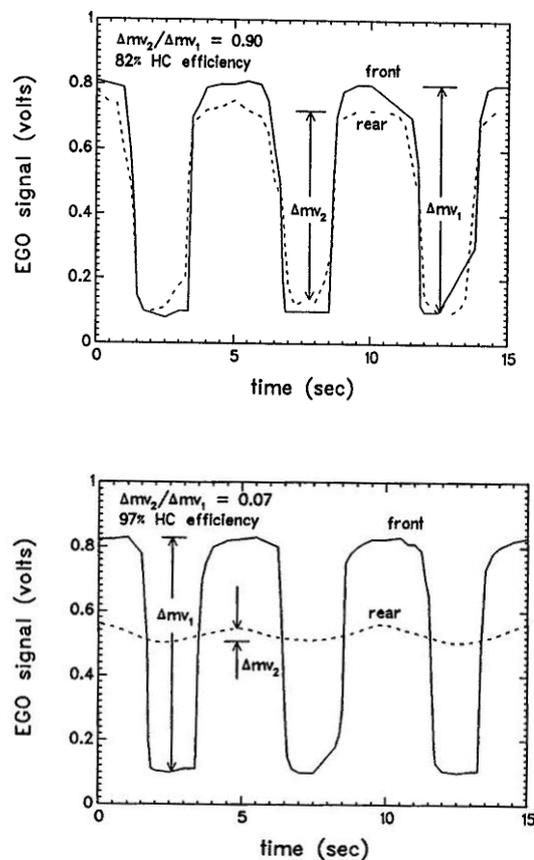
With introduction of TWC (or catalyst) technology and its usage in emission system of vehicles, toxic emissions were reduced effectively and more sophisticated emission standards were reached.

Most of light duty vehicles use TWC formed in a honey comb structure, presenting more surfaces for catalytic reaction to improve its performance. Monitoring this performance has always been a major challenge due to its complicated behavior. TWC may lose its performance for different reasons where two majors are thermal aging and poisoning by lead and sulphur oxides. If any of these two happen, TWC performance will drop leading to a dramatic increase in emission. Therefore, catalyst monitoring is very crucial and has been forced by legislation since 1996 in the US and 2000 in Europe. Since then, model-based TWC monitoring has gained a lot of research interest, where modeling TWC performance has been a key element.

Peyton Jones [2] presented a model for TWC which is used for onboard monitoring. He used A/F ratio before and after TWC to monitor its performance. The only point is usage of linear lambda sensor downstream TWC which is not available on conventional on-road vehicles. Akcayol [3] used a 2-layer N.N to model HC, CO and gas temperature downstream TWC during NEDC. The only input to their model is the time after engine start limiting its application to specific situation in which it is trained in. In fact they did not consider any dynamic for TWC behavior (which is highly dynamic). In [4] Gliemllo et al. combined N.N with GA to compute stoichiometric coefficient for main reactions in TWC. Then, they calculated emission species after TWC using their concentration before it. Despite good estimated results, their method implies gas analyzing facilities. Botsaris [5] estimated emission gases during cold start. Input to their 2-layer network is the temperature difference between TWC input and output and its output is concentrations of CO, CO<sub>2</sub> and HC in exhaust pipe.

The great effect of TWC performance on downstream nonlinear oxygen sensor, called LSF hereafter, output volt-

age has made this sensor the main element for TWC monitoring. The effect of TWC aging can be observed clearly in the sensor behavior (fig. 1). Therefore, estimation of LSF output voltage can be of great usage in TWC monitoring.



**Fig 1.** Effect of TWC aging on LSF output. Up: Aged TWC. Down: new TWC [6]

In this paper, LSF output voltage is estimated using NARX model of emission control system. The estimation algorithm includes modeling both TWC and LSF. Making it very useful, this method can be used for conventional vehicles without adding any sensor to the vehicle. In section 2 NARX model structure is introduced. Section 3 addresses emission control system and modeling methodology. Section 4 explains about experimental setup and test procedure in which real data are measured from vehicle. Section 5 illustrates NARX model structure and its training algorithm. Finally in section 6 estimation results are depicted and compared to measurement data and results are discussed. The possibility of using the model as a monitoring algorithm is also investigated in section 6.

## 2- NARX Model, Description of Structure

After being successfully used in many applications like signal processing and nonlinear system modeling and control, artificial neural networks (ANN) has received great attention in recent years. Their outstanding features like nonlinearity, adaptivity, evidential response, fault tolerant ... made their usage interesting in many engineering applications. For example in [7] a combination of NARX model and ARMA (autoregressive moving average) model is used to obtain a forecasting tool for long term machine state monitoring.

In another industrial application, heavy-duty power plant gas turbine states including compressor discharge pressure, exhaust gas temperature and electrical power are estimated by a NARX structure in [8].

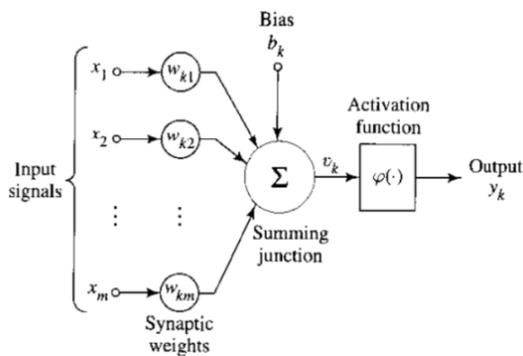


Fig 2. nonlinear model of a neuron[9]

A neural network is a massively distributed processor made up of simple processing units (neurons, fig.2) connected to each other through weighted connections. These weights are modified in a process called learning algorithm in a way to attain a desired design objective [9].

In 1962, model neurons connected to each other in a simple fashion were given the name “perceptron” by Rosenblatt. Combined in many layers, multi layer perceptron (MLP) was shaped and used for simulation of physical systems.

When a neural network consists in one or more feedback, it is called recurrent neural network (RNN). The feedback may come from the output layer or from a hidden layer of the network to the input layer. Generally, there are two functional uses of recurrent networks: associative memories and input-output mapping. This paper deals with using RNN as an input-output mapping for a highly dynamic system (TWC and LSF).

The architecture layout of a recurrent network takes many different forms, one of which is input-output recurrent model (fig5). This structure (in our study) includes a static MLP as its core, inputs that are applied to tapped-delay-line memories as well as output which is fed back to the input via another tapped-delay-line memory. This recurrent network is also referred to as nonlinear autoregressive with exogenous inputs (NARX) model. The dynamic behavior NARX model is described by

$$\begin{aligned} &U_1(n), \dots, U_1(n-p+1), \\ &U_2(n), \dots, U_2(n-p+1) \\ &y(n+1)=F(Y(n), \dots, Y(n-m+1)) \end{aligned} \quad (1)$$

Where F is a nonlinear function of its arguments [9].

## 3- Modeling Engine Emission Control System Using NARX Model

### 3-1- emission control system, hardware description

General structure of a typical emission control system in gasoline spark ignition engines is shown in fig 3.

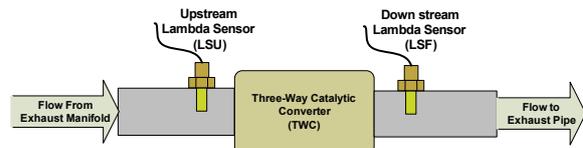
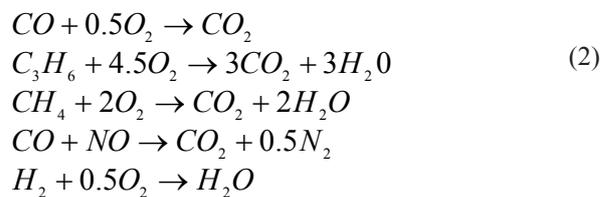


Fig 3. Emission control system in a gasoline SI engine

As exhaust gases from combustion chamber flow over TWC surface, oxidation and reduction reactions take place to reduce the toxicity of emissions. The main reactions in TWC are:



Using two oxygen sensors, ECU gets some evaluation of exhaust gases upstream and downstream of TWC. The first sensor which is located upstream catalyst, called LSU here after, can measure air fuel ratio (or equivalently, lambda) in a wide range (from  $\lambda=0.7$  to 2.4). This linearized measurement is used as the feedback signal in engine lambda control.

on the other side, downstream catalyst, another oxygen

sensor, LSF, behaves in an almost-binary manner depending on air-fuel ratio of exhaust gases. The output voltage of this highly nonlinear sensor (fig 4) is used mainly for NOx control and TWC monitoring.

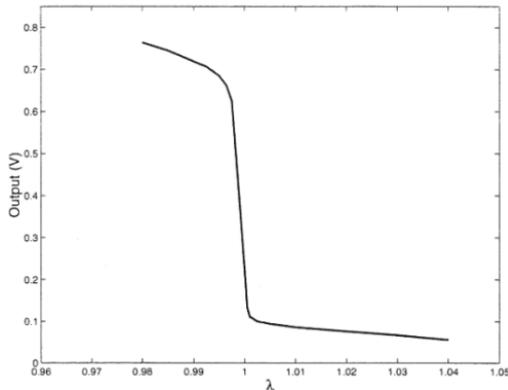


Fig 4. Typical output voltage of a LSF

### 3-2- Emission Control System, Model Description

The main focus of this paper is to estimate output voltage of LSF using a NARX model of TWC and LSF. Structure of desired network is depicted in fig 5. An important step in modeling is detecting model inputs, which means finding the most influential terms on LSF output considering TWC and LSF behavior.

TWC is a hybrid system with different behaviors in different modes. In picture 6, different modes of TWC are illustrated using LSU and LSF signals. In mode I, TWC (in fact CeO<sub>2</sub> in monolith) stores extra oxygen in exhaust gas flow. When TWC goes to lean saturation in mode II, no more oxygen

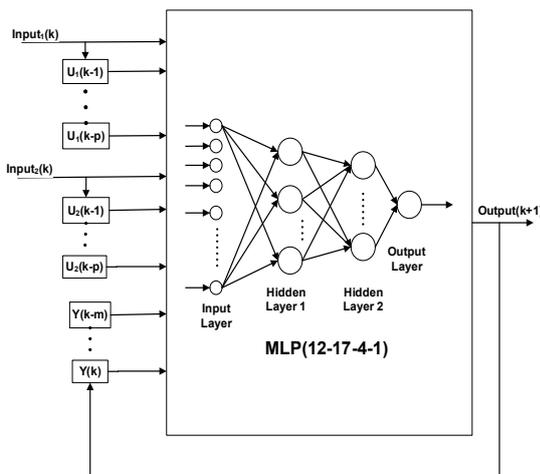


Fig 5. NARX structure used for estimation

can be stored by TWC and exhaust gas upstream and

downstream finds the same concentration in its elements. By reducing lambda in exhaust flow, unburned gas flows over monolith surface and use stored oxygen to completely burn (mode III). As more fuel-rich gas enters TWC in mode IV, all stored O<sub>2</sub> are consumed and TWC goes to its rich-saturation mode (where no more stored O<sub>2</sub> is available).

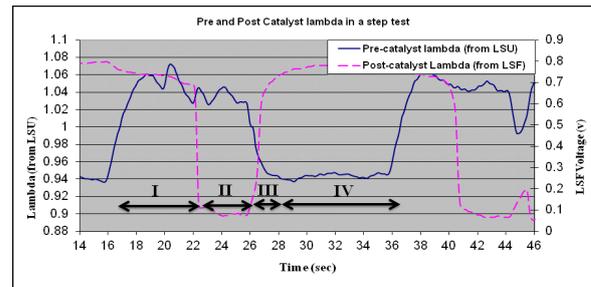


Fig 6. input-output behavior of catalyst in different modes

Figure 6- Many researchers worked out estimation models for TWC. Peyton Jones et al. [11] describe downstream  $\lambda$  as a function of oxygen storage capacity (OSC) and hydrogen concentration in water-gas shift reaction (fig7), which are functions of upstream  $\lambda$  and gas flow over TWC.

Fiengo [12] describes TWC as a 1-order filter which filters upstream  $\lambda$  depending on catalyst OSC at the same moment.

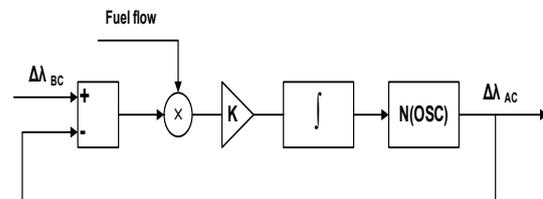


Fig 7. approach to model downstream lambda by [8]

He tried to estimate OSC from fuel flow and  $\lambda$  upstream ( $\lambda_{BC}$ ) and downstream ( $\lambda_{AC}$ ) TWC. Briefly speaking, he assumes  $\lambda_{AC}$  as a nonlinear function (f) of  $\lambda_{BC}$  and OSC. OSC is also calculated as the rate of consuming and storing oxygen as:

$$\frac{d(OSC)}{dt} = f(\dot{m}_{gas} * \Delta\lambda_{BC}) \tag{3}$$

In which  $\dot{m}_{gas}$  is gas flow over TWC and  $\lambda_{BC} = \lambda_{BC} - 1$ . In 3 when the mixture is fuel-rich ( $\Delta\lambda_{BC} < 0$ ), oxygen is released, but as  $\lambda$  increases to fuel lean region, oxygen is stored in TWC.

Therefore one can conclude the main parameters entering NARX model are  $\lambda_{BC}$  and gas flow over TWC (fig8).

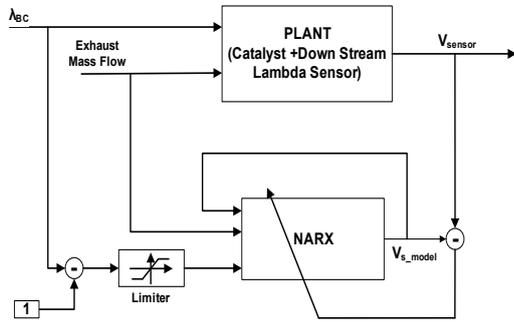


Fig 8. used series-parallel structure to train NARX

When the main input parameters to model are detected (which are  $\lambda_{BC}$  and exhaust gas flow), another required term in NARX network is time delays for each input. This is a crucial term because catalyst acts as a filter changing magnitude of fluctuations and setting delays to its inputs. TWC action as a filter changes based on its input history. For example, when it has a good oxygen storage, the filtering is done very well in rich zone but as it loses all stored  $O_2$ , TWC filtering is reduced to a simple delay (fig. 9). Two main filters are considered for emission control system in this paper. The first one is LSF dynamics (a 1<sup>st</sup> order lag). Second is dynamic of TWC (due to its internal chemical reaction). To detect the order of this filter considering model simplicity/ realizability (low order filter) and its precision (high order filter) after different simulations  $m=5$  and  $p=2$  are selected (fig. 5). Therefore, final structure of NARX is as 12 nodes in input layer (for 2 inputs and one feedback variable), 17 neurons in 1st hidden layer and 4 neurons in 2<sup>nd</sup> hidden layer and 1 neuron in output layer.

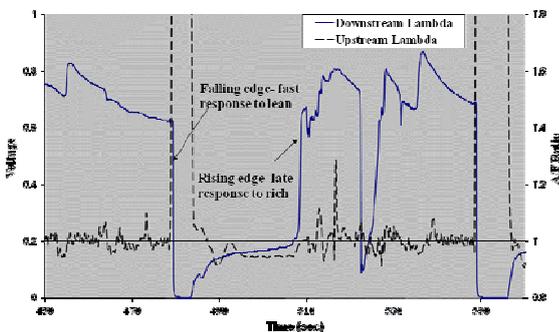


Fig 9. dynamic behavior of TWC and LSF

### 4- Experimental Setup and Test Procedure

Naturally, TWC performance is evaluated on a standard driving cycle (like NEDC, FTP...). In this research, NEDC is decided to be the main evaluation driving cycle (fig. 10). Moreover, two general driving cycles in which there is no specific driving pattern are also used as evaluation tests. LSF output voltage is measured from EF7 engine integrated into SAMAND vehicle on a Horiba chassis dynamometer. Using INCA [14], ECU measurements and calculations are stored during NEDC with a frequency of 100 Hz. The stored data is used for NARX network evaluation. The NARX model is realized in MATLAB on a dual core 2.6GHz computer. The whole drive cycle (which is 900 seconds) is simulated in 0.4 second.

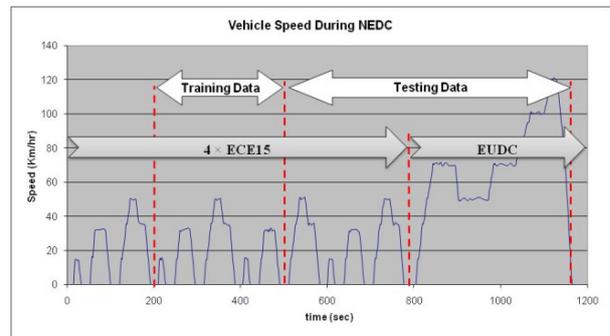


Fig 10. training and test period for NARX

### 5- LSF Output Voltage Simulation

As it was described in section 4, a NARX structure as 12-17-4-1 is used. Its output is LSF simulated voltage and its inputs are 10 delayed elements of  $\lambda_{BC}$  and exhaust gas flow and 2 delayed elements of output feedback (fig. 5). Training method is error back propagation using the steepest descent. The cost function is:

$$E_p = \frac{1}{2} \sum_1^K (D(k) - out(k))^2 \tag{4}$$

Where  $D(k)$  is sensor measured output,  $out(k)$  is estimated output by NARX,  $k$  is pattern number and  $K$  is total number of training pairs. To train the network efficiently, we decided not to use data from first ECE cycle (0-200sec in fig. 10). The reason for this decision is the great effect of temperature on TWC performance. Moreover, during the initial part of this period, LSF heating is not finished and its voltage is not reliable.

Of the remaining part during NEDC, 34% is used for training (fig 10). Tangent hyperbolic (tanh) is used as ac-

tivation function in the first layer. In the second layer, because of the similarity between LSF output voltage (fig.3) and sigmoid function, it is used as activation function:

$$\varphi(v) = \frac{1}{1 + \exp(\alpha.v)} \quad (5)$$

Batch training is used to train NARX network. Reaching error limit or specific number of epochs was assigned as training termination criterion. It is worth mentioning that pattern-by-pattern methodology cannot be used as train algorithm (due to system dynamics). So, batch back propagation (BBP) is used to as perceptron training algorithm which also guarantees avoiding forgetting phenomena.

To assure convergence of network, an adaptive learning rate is used as:

$$\zeta(k+1) = \zeta(k) + \alpha \times (\log \text{sig}(-E(k) + E(k-1)) - 5) \quad (6)$$

Where  $E(i)$  is network error at the end of  $i$ th epoch and  $\alpha$  is a factor limiting change rate of  $\eta$ . This selection forces  $\eta$  to get its highest convergable value maximizing convergence rate and removing possibilities of being trapped in local minimum.

### 6- Results and Discussion

In this section LSF output calculated by NARX is compared to its real value from measurement. Four tests were conducted. The first one was on a vehicle with new TWC while the second test was conducted on the same vehicle 3 months later when the catalyst was aged by more mileage. Input data to NARX model ( $\lambda_{BC}$  and exhaust gas flow during NEDC) during these two tests are shown in figures 11 and 12.

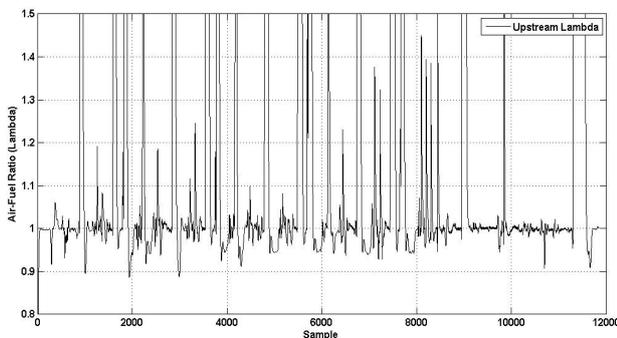


Fig 11. NARX input:  $\lambda$  before TWC

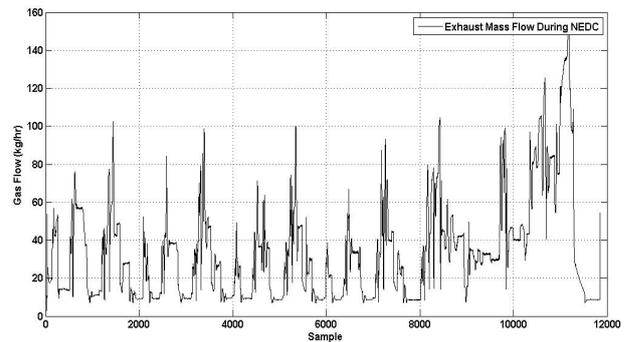


Fig 12. NARX input: exhaust flow (calculated by ECU)

In figure 13, NARX results for LSF voltage and those from measurement are depicted in training zone (samples 0 to 3000) as well as in test region (samples 3000 to 9300). Estimation error ( $|NARX\_output - measurement\_data|$ ) is also plotted. During the first part of emission cycle (ECE15) despite highly stochastic inputs to NARX and highly nonlinear behavior of TWC and LSF, NARX network gives an acceptable estimation. The error increases in highly transient conditions (between samples 4100-4300 as an example) due to high switching between lean and rich.

In the second part of driving cycle (EUDC, samples 6000 to 9300), when transient driving conditions are fewer, LSF output is estimated much better compared to the first part (ECE15).

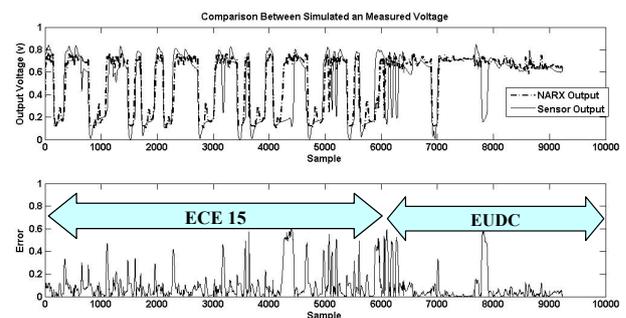


Fig 13. Up: Estimated (dashed) and measured voltage of LSF (in test with new catalyst). Down: error percentage

To investigate the ability of model for catalyst monitoring, further testing of desired network is done during another NEDC using the same vehicle 3 months later when the TWC was aged more by vehicle mileage (fig 14). Clearly the estimation error has increased almost in all parts of the cycle (especially during ECE15) indicating a deviation of TWC from a new (not aged) catalyst. To show this more

clearly, an integral index ( $I_{index}$ ) is defined as

$$I_{index} = 0.5 \sum_1^{end} \|V_{narx(i)} - V_{sensor(i)}\|^2 \quad (7)$$

Where  $V_{narx}$  is estimated voltage and  $V_{sensor}$  is measured voltage. Table (1) compares  $I_{index}$  for new (fig. 13) and aged (fig. 14) catalyst. Clearly estimation error has increased when catalyst is aged.

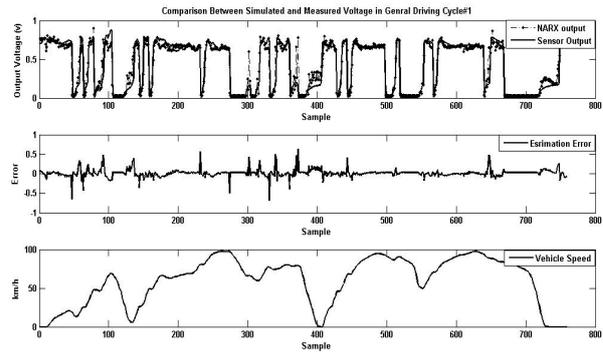
**Table 1.** Integral index for estimation error

	$I_{index}$
New catalyst	116.15
Aged catalyst	143.97

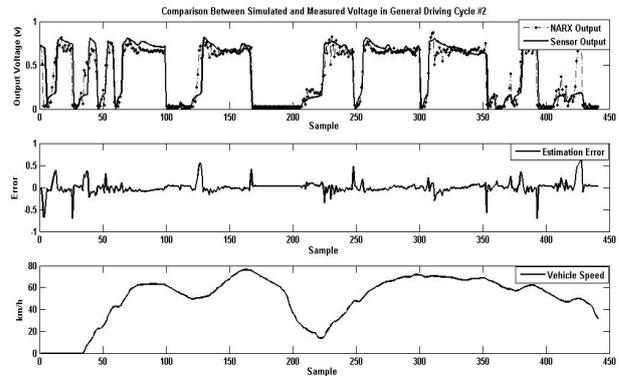
Finally, performance of the designed strategy was evaluated for two general driving cycles. The effective estimation of algorithm during these two cycles is shown using figures 15 and 16 where estimated voltage and estimation error as well as vehicle speed during test cycle are depicted.

### 7- Conclusion

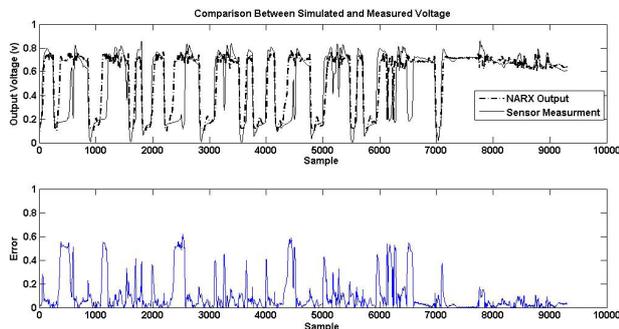
This paper proposed a NARX model to simulate after catalyst nonlinear oxygen sensor output voltage. Upstream  $\lambda$  and ECU calculated exhaust gas flow are only inputs to the modeling system. Results compared to measured data reveal good estimation by NARX model. Also model ability to detect TWC aging was demonstrated by testing the same vehicle equipped with an aged catalyst. Results indicated more deviation between modeled and measured data when catalyst was aged.



**Fig 15.** Evaluating performance of estimation algorithm during a general driving cycle



**Fig 16.** Evaluating performance of estimation algorithm during a general driving cycle



**Fig 14** Up: Estimated (dashed) and measured voltage of LSF (in test with more aged catalyst). Down: error percentage

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