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Model Based Diagnosis of Oxygen Sensors

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Abstract: Automotive industry targets such as complying with emission legislations and increasing fuel economy, require the improvement of air-fuel ratio control systems. Oxygen sensors are a crucial part of these control systems and regulations oblige monitoring of their performance and detecting sensor-related faults. The primary purpose of this paper is to develop a methodology for precise and accurate monitoring and diagnosis of oxygen sensors to meet legislations and performance targets while the required calibration effort is reduced. Input parameters with the highest correlation factors were selected to be utilized in different system identification methodologies to statistically determine the most fitting model. In the end, a NARX model with two hidden layers and eight neurons in each hidden layer with standard deviation and mean threshold values was determined to be the optimum design to detect if the oxygen sensor was functioning or faulty.

Keywords: Oxygen sensor monitoring, OBDII, System identification, data-based control, model based diagnosis, artificial neural network, NARX, residual generation.

1. INTRODUCTION

Emission legislations require efficient combustion to take place in the cylinders of Internal Combustion Engines (ICEs) and conversion of poisonous combustion residues into harmless exhaust gases through the after treatment systems. Institutions like California Air Regulation Board (CARB) and Environmental Protection Agency (EPA) enforce On Board Diagnostic (OBD) Systems to monitor factors which affect combustion efficiency and emissions. The air-to-fuel ratio (AFR) is one of these factors. Optimum trade-off between engine power, fuel economy, and emissions can be achieved when AFR is equal to the theoretically required value for complete combustion which is the stoichiometric ratio, $(A/F)_{stoch}$ (Robert Bosch GmbH 2014). Lambda, λ, is the ratio which quantifies how much the actual AFR deviates from the stoichiometric ratio (1).

$$\lambda = \frac{\left({}^{A}/_{F}\right)}{\left({}^{A}/_{F}\right)_{stoch}} \tag{1}$$

In lean condition ($\lambda>1$), air-fuel mixture contains less fuel than it would need for complete combustion, so there will be an increase in combustion temperature, emissions (particularly NOx), and probability of engine knock, with a decrease in engine power. If the engine is running in rich condition ($\lambda<1$), the air-fuel mixture will contain more fuel than that can be oxidized by air, so there will be an increase in emissions (especially HCs and CO) and fuel consumption.

To calculate the AFR and implement the required lambda, a control system consisting of a set of sensors is required. Also,to monitor the performance of the three-way catalytic converter (TWC), two oxygen sensors (also called lambda sensors) are placed in the exhaust system, one upstream and the other downstream of the catalyser (Robert Bosch GmbH 2014). This way, the degradation of the catalyst efficiency can be monitored by a control system (Moriya et al. 2001). For the TWC to perform an efficient conversion, the exhaust gases should stay within specified tolerances of $(A/F)_{stoch}$ and the catalyst should operate at a specific temperature range. Also, the primary sensor located upstream of the TWC monitors the concentration of residual oxygen within the exhaust gases of the ICE to calculate the current AFR and dynamically tune the consequent AFRs. This is crucial for both combustion efficiency control and TWC monitoring (Robert Bosch GmbH 2014). In addition to failing the emission tests, a malfunctioning oxygen sensor with a wrong AFR implementation can cause more than 15% increase in fuel consumption.

For these reasons, EPA and CARB require OBD systems to check oxygen sensors for two different fault cases. Transient-time fault induces a reduction in signal amplitude and a slower response to the changes in the gradient of the signal. Response-time fault causes the signal to shift to the left along the time axis due to the retarded reaction of the sensor.

To reduce the risk of sensor output faults, control systems use sophisticated measuring equipment. While there are several different types of oxygen sensors to regulate AFR and monitor TWC performance (Lee 2003), two of these models are generally put in practice. One of them is the Heated Exhaust Gas Oxygen (HEGO) sensor, also known as switched type or

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binary oxygen sensor. The output signal of this type reveals whether the combustion was rich or lean. The second most common sensor type is the Universal Exhaust Gas Oxygen (UEGO) sensor, also known as wideband oxygen sensor. Using relatively newer technology than a HEGO sensor, it gives the lambda value as the output. Using a UEGO sensor as a substitute for a HEGO in the exhaust system makes a great contribution to the AFR control algorithm (Heck et al. 2001).

To have accurate control over lambda values, an efficient model should be designed to process and analyse the data from the oxygen sensors and to react to the outputs. For this, system identification should be done correctly to provide a characterization of the behaviour of the system and internal dynamics such as delays, speed, oscillations, and disturbances by correlating inputs to the outputs.

Principal component analysis (PCA) is a method to identify the required inputs and outputs of the model by utilizing Q-statistic and/or squared prediction error estimations. Components with larger variance correspond to greater dynamics whereas lower variation corresponds to noise (Ballabio 2015). A study by Wang et al. found out that a single PCA model is not enough to be able to detect all sensor failures and it is important to use extensive PCA models in parallel (2004).

Fault detection and diagnosis methodologies can be grouped into two main subcategories called model-free and model-based fault diagnosis. Model-free methods rely on system characteristics and heuristics approaches to decide if the system is running faulty or as expected. A signal based diagnosis approach analyses the affected system by using signal processing techniques and filters to decide if the system is functional or faulty (McDowell et al. 2007; Al Ahmar et al. 2010; Abbas et al. 2007). A diagnosis method similar to the signal based method is the plausibility check, since it uses sensor output signals against physical laws without considering the dynamic relations between system variables for fault detection (Versmold et al. 2006). Physical redundancy approach utilizes several sensors to measure the same physical quantity therefore it is a complex, costly, and bulky method (Wang et al. 2004).

Model-based methods mostly use mathematical models to compare the outputs of the model to those of the actual system. One of the most popular model-based methods is the knowledge-based model. Results taken from direct redundancy and nonlinear diagnostic observers along with mean value model for getting residuals can be evaluated using fuzzy thresholding in the diagnosis of air intake systems (Nybarg et al. 1997). Structured hypothesis testing is another methodology in which observers are used to calculate error parameters (Nyberg et al. 2004). Analytical models can be examined by separating the system into several groups such as parity relations, observers, and parameter estimation methods, such as sliding mode observers or Kalman Filters. In the structured parity equation approach, inputs such as sensor bias, actuator bias and disturbances coming from simulation data, are used to get residuals in the system on the purpose of online detection of sensors and actuator faults in automobile engine (Gertler et al. 1993). UEGOs have nonlinear characteristics and a suitable method to detect misfiring faults in nonlinear systems is using sliding mode observers, as used by Wang et al. (2005). Also, using extended Kalman filter for estimating fuel film dynamics in the intake port of an SI engine gives a good performance in predicting AFR (Arsiea et al. 2003). To overcome the experimental and computational workloads and decrease the complexity of physical equations, applying data-driven methodologies can be another solution. Fuzzy-based pattern recognition method for real-time detection of abnormal injection pressure patterns is another approach revealed in the literature (He et al. 2004). Neural network modelling provides solutions for nonlinear and complex systems with less a priori knowledge of the plant dynamics. It just requires the behaviour of the system to be modelled, with no need for any physical modelling since it is able to learn by different learning algorithms (Purwar et al. 2007). The basic processing unit of a neural network is called a neuron. A neural network is made of highly interconnected, identical or similar neurons organised in layers. The structure consists of hidden layers with input and output layers at two ends. Specific weights representing the strength of connections between the neurons are added to each connection and each input. The corresponding connection weights are multiplied with all the inputs to compute the state when the neuron is activated. Additionally, a separate extra weighted input, called the bias, is included and it is a constant value of one. Even though there are many different algorithms available to train a Neural Network, only four of them are used to compare the performances in this study. These are Levenberg-Marquardt Backpropagation (LM) algorithm, Gradient Descent with Momentum and Adaptive Learning Rate Backpropagation (GDX) algorithm, Bayesian Regularization Backpropagation (BR) algorithm, and Scaled Conjugate Gradient Backpropagation (SCG) algorithm. LM is a second-order numerical optimization technique combining features of Gauss-Newton and steepest descent algorithms. The performance of GDX training algorithm depends on the learning rate and the momentum coefficient. BR training algorithm overcomes overfitting problems by considering the amount of fitting along with network architecture. It minimizes the combination of squared errors and weights to determine the appropriate combination. SCG training algorithm does not need several output computations for each training input which makes it faster (Gopalakrishnan 2010). An example of the recurrent neural network (RNN) model is proposed to predict the AFR to be used in closed loop fuel calculation, and diagnostic application in a port fuel injection spark ignited engine (Arsie et al. 2007). The selection of a proper number of hidden layers and an adequate number of neurons is a significant problem to have a good model. In case of less hidden layers and neurons than necessary, considering the complexity of the system, the model might fail to meet the target output on a large scale of the data. This case is called as underfitting. On the other hand, the case of having too many hidden layers and neurons might cause overfitting. Overfitting causes to have output values that are so tightly fit a limited set of input data. Therefore, such model might have issues to fit another additional data set other than training data. Trial-and-error method is used to define the numbers of the hidden layers and neurons by starting with small numbers of neurons and hidden layers and then increasing the number with relation to the results. These attempts continue until getting sufficient model outputs (Panchal et al. 2014).

The nonlinear-autoregressive-exogenous model (NARX) is a type of feedforward neural network. The NARX network is used to model time series as a special form of the linear ARX model (Beale et al. 2010). This model relates both past and current values of the inputs as well as the past values of the time series to the present output of a time series (Beale et al. 2010).

A way to model the UEGO sensor dynamics is considered as a linear response around stoichiometry and approximated by a first order transfer functions with a delay (Germann et al. 1996). The ECU has an outer control loop providing the set-point value of AFR to the inner control loop which keeps the AFR at this value by using feedback from UEGO sensor (Okazaki et al. 2009). Even though the feedback component is slower than feedforward, feedback decreases the steady-state error between the desired AFR and the actual AFR. Also, the delay between the injection of a fuel-air mixture into the cylinder and the time it is observed at UEGO sensor due to the combustion dynamics and exhaust gas transportation is considered (Yildiz et al. 2008).

The residual evaluation algorithm directly affects the performance of fault detection. Several ways were studied in the literature for robust residual assessment. Statistical data processing, adaptive thresholds, fuzzy clustering, pattern recognition data correlation are some of the standard residual evaluation methods (Frank et al. 1997; Isermann 2006; Svärd et al. 2014; Patan 2008). To evaluate the performance of a model, statistical methods can provide a good way to separate different sensor faults under different operations. This approach requires modelling the distribution function from the differences of consecutive sensor measurements and their parameters. It also needs to model a probability density function (Jammoussi et al. 2013). This involves two different steps based on the operation. In the first step, parameters which belong to the distribution function in case of asymmetric operation are calculated. Considering these parameters, a decision is made whether a fault exists. To be able to specify the fault type, a system identification process is applied for the case of symmetric operation in the second step. According to central peak and shape of the distribution functions, the type of the operation can be defined.

2. METHODS

The UEGO sensor used for this study was Bosch LSU4.9. It was located between the turbocharger and the TWC in the exhaust line. At the exit of TWC, there was a Gasoline Particulate Filter (GPF) followed by a HEGO sensor (Fig. 1). Data were taken for a light duty gasoline vehicle running steady state and transient cycles such as Worldwide Harmonized Light Vehicles Test Cycle (WLTC) on a chassis dynamometer. In one set of measurements, a functional UEGO sensor was used while in the other set a malfunctioning sensor was used. To collect data from the vehicle, ATI Vision was used as calibration software.

To start with the system identification, system inputs had to be determined. General parameters of combustion dynamic, physics of the system, and the ideal gas law were considered to determine which inputs could have major effects on the output. After deciding on possible input parameters, Principal Component Analysis (PCA) method was applied to see which variables had the strongest correlation to each component. These variables were taken as final inputs for the system identification process. In this study, PCA Toolbox for MATLAB, developed by Ballabio, was used for the analysis of the input data(2015).

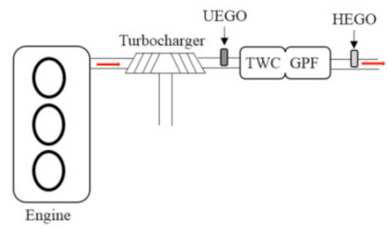

Fig. 1. Illustration of the experimental setup.

Data from the chassis dynamometer were plotted and checked manually to see if there were any outliers in the data. The Fourier Transform Analysis was used to determine the range of noise and found to be in the 2.4-2.5 Hz range. Both input and output data series were normalized to a common scale to nullify the effect of the differences in signal magnitudes on the model's performance. Z-score normalization method was used for each input and output since it increases accuracy and produces faster results (Sola et al. 1997). Means, offsets and linear trends were removed from the data by detrending to eliminate the random differences between the input and output levels.

First, Linear System Identification methods were tried due to their simplicity. Impulse response model, state space model, and auto regressive exogeneous (ARX) model with different orders were inspected. System delays for each approach were calculated to be compared to the raw data.

After that, nonlinear system identification methods namely Neural Networks (NN) were used to obtain a reasonable model. At this step, model order and model delay estimations were calculated as well. Various input combinations were tried next to different model structures. Processed data from chassis dynamometer were split into three parts to train, validate, and test the Neural Network model. The first 70% of the dataset was used to train the network while the next 15% was used for validation and the last 15% was used for testing. Then by using trial-and-error, the NN model with the highest correlation performance was selected.

During the training phase of the neural network, an open loop structure incorporating an additional input parameter for delayed target data was used. In the open loop network structure, the output was generated based on the common time extent of the input signals and target output data. To be able to use the model with other datasets of a functional and damaged sensor, the model was converted to a closed loop system. The main neural network's number of neurons and hidden layers as well as training method were modelled by using steady-state data in different operating points of engine speed and torque.

Residual generator collected the output signals of the actual component and model for a specific range of time or event and calculated the error between these two signals. During residual generation, this steady-state data-based model was used with the two sets of data coming from WLTC. The first data-set was the one with a good oxygen sensor and the second was with a faulty sensor.

Then, residuals from the residual generator were analysed for decision making. Residual evaluation was based on comparing the residual distributions with mean and standard deviation thresholds to detect faulty sensors. These thresholds were derived from the European legislation, EOBD, by taking transient-time and response-time faults into account. Calculations of mean and standard deviation wereperformedon 50 samples taken after the enabling of the monitoring function. An appropriate area was chosen on the WLTC, and comparisons were made for that specific operating region to see if the sensor was functioning or not.

3. RESULTS AND DISCUSSIONS

System physics and the ideal gas law yielded the general system inputs as vehicle speed, engine speed, torque, air mass, fuel mass, intake manifold temperature and pressure, throttle valve position, Mass-Air-Flow (MAF) output, rail pressure and lambda controller output. However, employing PCA results and combustion dynamics narrowed down the input variable list to air mass, fuel mass, MAF output, rail pressure, intake manifold pressure, intake manifold temperature and lambda controller output. The only output of the system was the output of the UEGO sensor.

When the performance values of linear models were calculated, they reached a maximum of 40% which is inadequate (see Fig.2). Splitting the data into different speed ranges gave a maximum model performance value of 50% which is still not acceptable. In ARX models, the degree of unexplainable output variance indicates the shortcomings of the model. Comparing the results of minimizing sum of the squares, Rissanen MDL criterion, and Akaike AIC criterion, it was seen that minimizing sum of the squares led to the most accurate ARX model. However, it was still not an acceptable level. There might be several reasons why these linear systems gave insufficient results. ARX and state-space models are linear models . Disturbances can also have a significant impact on the system, so their exclusion makes linear models inadequate. Higher order models can be required. For these reasons, it was seen that the nonlinearities in the system could not be modelled with linear system methodologies.

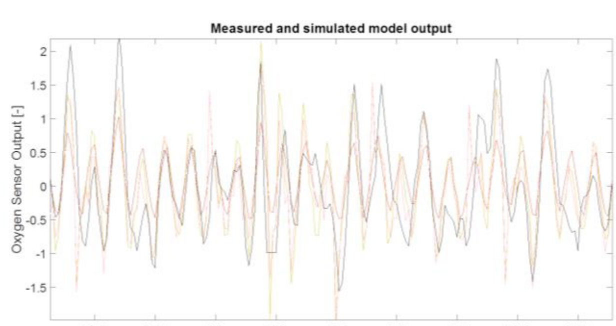

Fig. 2: Best-Fit Analysis for Linear Models.

Therefore, nonlinear system identification methods were chosen over linear ones. NARX neural network-based model of the oxygen sensor was understood to be the fundamental component for a residual generator (Fig. 3). The system delay was calculated as three and this was validated using the raw dynamometer data. Therefore, the first delay value in neural network structure was taken as three. Afterwards, the delay value was increased to 5 and 8 to see if the system is improved. Different training methods,numbers of neurons and hidden layers were tried to see which design had the highest convergence.

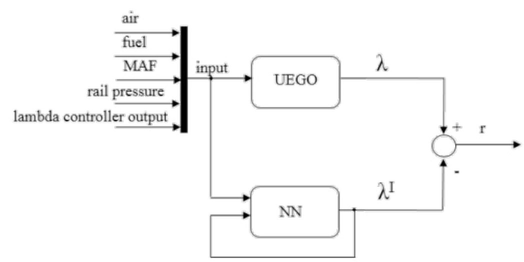

Fig. 3: Residual Generator.

In Figure 3, λ stands for the actual output of oxygen sensor on the vehicle, whereas λ^Irepresents the model output. The residuals were generated by,

$$r(t) = \lambda(t) - \lambda^I(t). \tag{2}$$

The magnitude of residuals had to be large enough and they had to last long enough so that decision for fault detection could be made robustly (Fig. 4).

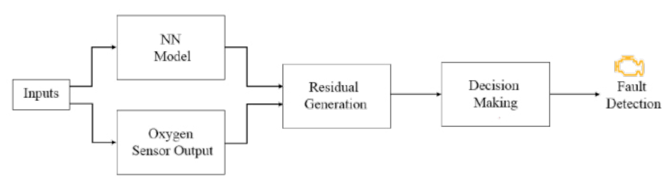

Fig. 4: Block diagram of residual generation and evaluation process.

The bar chart on Figure 5 shows the correlation coefficients which refers to the relationship between the inputs and the output for 29 models. These values range from 0 to 1 with 1 indicating perfect correlation and 0 indicating poor correlation. While choosing the best-fit model, a trade-off between overfitting to training data and underfitting to test and validation data must be considered. If the accuracy of the training data set is increasing, but the accuracy of validation dataset stays the same or decreases, that means the current neural network structure overfits. In addition to correlation coefficients, mean squared error (MSE) calculation is used to measure the performance of the model structure (Fig. 5). A smaller MSE value indicates a better fit. For a delay of three and learning rate of 0.2 with 10 neurons and 1 hidden layer (models 1, 6, and 10), Levenberg-Marquardt-Backpropagation (LM) gives higher correlation and lower MSE values with respect to Adaptive-Learning-Rate-Backpropagation (GDX) and Bayesian-Regularization-Backpropagation (BR) for this application. On the other hand, for a delay of five and learning rate of 0.2 with 1 hidden layer (models 13-16), it is seen that there are no significant differences in the performance of LM and Scaled-Conjugate-Gradient-Backpropagation (SCG). In this case, LM is recommended due to the speed of data processing. When the delay is five with 2 hidden layers (models 17, 19, 20), it is seen that increased learning rate improves the correlation coefficients for training dataset, but also decreases the performance of test and validation sets. Therefore, the learning rate is selected as 0.2. Also, it is observed that increasing the delay value from three to five enhances the performance significantly as past values of the system have a substantial impact on the results. Generally using two hidden layers instead of only one gives better correlations and lower MSE values. While deciding on the number of neurons, the optimization between overfitting and improved overall results should be taken into consideration. As a result, the model with a delay of 5, learning rate of 0.2, 2 hidden layers, and 8 neurons on each layer (model 27) is selected to use for model-based diagnostics calculations. It has the lowest value of MSE as 0.002 and highest correlation coefficients of 0.961, 0.952, and 0.905 for training, validation and testing respectively.

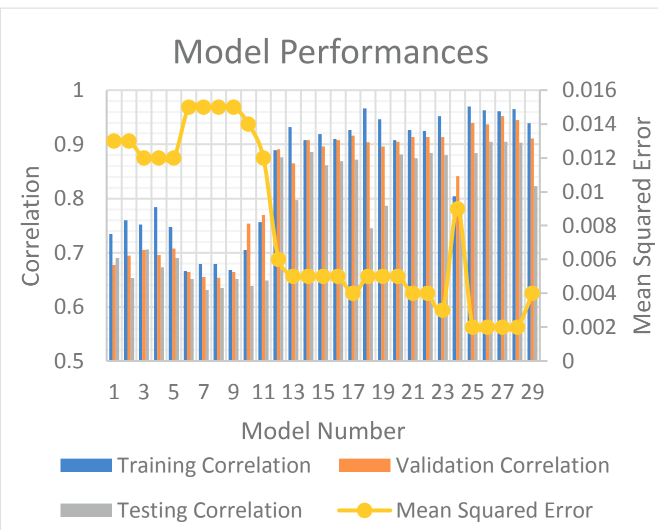

Fig. 5: Model Performance Values.

After deciding on the system identification method and designing the residual generator from model 27, residuals were evaluated as in Figures 6 and 7. From Figure 6 it can be seen that the model follows actual sensor outputs very closely with low residuals.

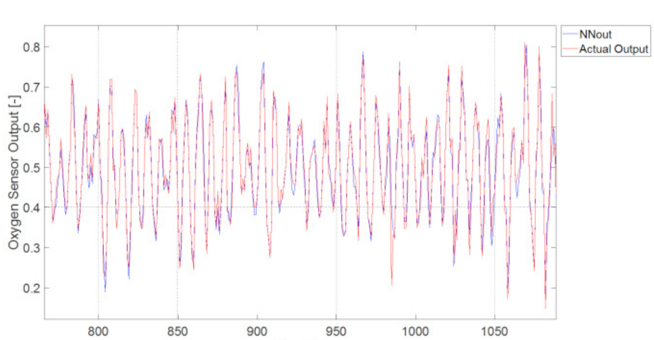

Fig. 6: Comparison of the model output and measured signal.

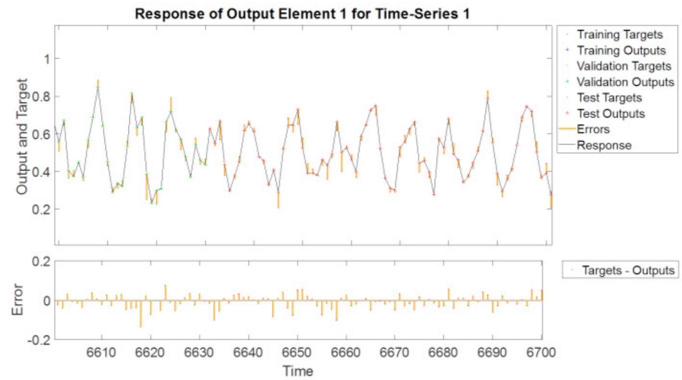

Fig. 7:Comparison of the model output and measured signal for test and validation data sets.

For fault detection two comparisons should be made as,

$$J_\mu \leq |\mu_r| \wedge J_\sigma \leq \sigma_r. \tag{3}$$

J_μ and J_σ are the mean and standard deviation thresholds and μ_r and σ_r are mean and standard deviation values from the data. If both thresholds are exceeded then the monitoring should identify the sensor as faulty.

In the ideal case, the residual is expected to be zero for a component or system with no fault. However, in real-practices, this is almost impossible. When the residual distribution for the functional sensor from the WLTC was analysed, the mean was around 0.05 and standard deviation was around 0.25. Unknown disturbances, dynamics that cannot be modelled, modelling errors, and the precision of input measurements cause non-zero residuals for adequately working components. Even though the residual from the functioning component is low, it might differ from zero due to these factors. For the malfunctioning sensor from the WLTC, residual distribution mean was around -0.5 and its standard deviation was around 0.85. The differences in the means and standard deviations of functioning and faulty sensors are high enough to differentiate. Therefore the results were as expected for a model with high correlation values.

4. CONCLUSIONS

This study has presented an accurate and compact design for a diagnostic system monitoring the oxygen sensor performance. It has been shown that by improving such data-driven model-based approaches, the behavior of the system dynamics can be achieved with no complicated calculations and high number of experimental data. Thus, it requires less effort and time to collect data and calibrate the monitoring function. The model based diagnosis approach is recommended for the cases where the component or system to be monitored has dynamic relations between system variables or needs several sensors to measure the quantity of the same physical feature, since data driven methodologies might help to overcome the complexity of physical equations and increased cost, especially for the nonlinear systems.

It was observed that, by means of Neural Network based methods, robust system models for a broad range of operating conditions can be obtained with no remarkable delay and with high accuracy. Using black-box approach, PCA was utilized to identify the most relevant inputs. NARX neural network model was used as a nonlinear system identification method. The best performance was obtained by using two hidden layers with eight neurons, while the system delay was five and the training algorithm was chosen as Levenberg-Marquardt. Consequently, the behaviour of the system dynamics which are close to the real system can be achieved with no complicated calculations and a high number of experimental data.

In further studies, the environmental conditions like temperature in hot and cold climates, different altitudes, or piece to piece variations can be considered while collecting data to build a more robust model. Also, more data can be gathered with sensors having different level of degradations. Regarding residual evaluation method, different approaches known in literature such as fuzzy clustering can be investigated to compare the performances.

As a continuation of this study, similar approach can be investigated in the diagnosis of Three-Way-Catalyst.

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