Ignition Timing Map Calibration Based on Nonlinear Dynamic System Identification using NARX Neural Network

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Abstract: The main topic of this paper is presentation of methodology for process identification and mathematical modeling of a nonlinear dynamic system, such as an IC engine, based on the experimental data acquired during base engine calibration in terms of ignition timing. With the introduction of certain assumption, mathematical model generated in this way could be used for verification of potentially optimal look-up tables and for look-up tables smoothing. For this type of time-series modeling, nonlinear autoregressive network with exogenous inputs will be used and full-factorial sweep of limited set of neural network parameters will be analyzed. Guidelines for mathematical model formation, verification and idea of stationary-based engine calibration will be briefly outlined. Comparison between measured and modeled engine torque will be shown alongside with instructions for further research on this topic.

Keywords: Dynamic testing, ECU Calibration, Engine testing, Neural network, Spark timing.

1. Introduction

Significant expenses, lack of available time and unavailability of engine test bench are three main reasons why mathematical modeling play such an important role during powertrain development. This paper and all of the analysis related to this topic are extension of the author's research started few year ago, with aim to develop powertrain unit for Formula Student racing car.

In the next few pages, it will be briefly described engine test bench features, test procedures, data post processing and analysis along with the idea of implementation of recursive neural network (NN) for control optimization [1] and further analysis of the dynamic model of the system. General guidelines for adjusting such a model do not exist in the literature, and the procedure is mainly based on trial and error method.

For the simplicity, the focus will be on the limited set of engine operating points and measured data. Only wide-open throttle (WOT) regimes will be analyzed, but the same principles could be implemented on partial engine loads.

2. Engine Testing

Base Engine Control Unit (ECU) control maps for ignition and injection were determined during testing of naturally aspirated air mass flow restricted Yamaha YZF-R6 engine. Various configuration of different intake and exhaust manifold concepts were developed alongside with 1D and 3D thermo-fluid-dynamic models, which were validated with aim to optimize torque surface over stationary engine speed – throttle input space (SPEED-TPS).

Engine mapping represents the process of getting data for injector opening time (INJ) and spark advance (IGN) look-up tables that give predefined value of air to fuel equivalence ratio (AFR) and maximal output power for the steady state operating regime, which is defined by the percentage of throttle opening and the engine speed [2]. For this purpose were used DTA S60 ECU with calibration interface which enables rapid manual change of control parameters.

3. Data acquisition

All additional sensor readings for effective parameters were set in time domain at 1 kHz sampling frequency. Readings from stock engine sensors, which were used as ECU inputs, and some output (control) parameters were available on the high speed ECU's CAN data stream (total of 24 channels). Established CAN communication enabled dataflow of all available ECU's data at maximum frequency of 50 Hz using CAN controller based on the National Instruments (NI) PXI hardware.

Serial communication between the ECU and PC allows real-time adjustment of engine control parameters (advance timing, injection duration and others) and monitoring of sensor readings (engine speed, throttle position, lambda sensor reading, intake air, coolant and oil temperature, intake air and oil pressure, manifold absolute pressure, battery voltage and others). Besides listed engine parameters, by using an open ECU interface, it was possible to adjust PID coefficients of all closed loop corrections and additional look-up tables (engine start fueling, idling, temperature compensations, etc.).

Along with the data acquisition, the NI PXI multifunctional acquisition devices were used for controlling and supervising of the engine test bench subsystems, like intake air conditioning system, engine throttle positioning, oil cooling and fuel supply system, evacuation of exhaust gases and additional engine cooling.

4. Data sets and post-processing

Engine control maps were generated at quasi-stationary operating regimes using dynamometer mode that limits the engine angular speed (upper boundary). This dynamometer operation mode is usually called "n-const" mode.

Because of relatively large number of test regimes time dedicated for exhaust temperature stabilization was minimized. Instead of waiting for the particular operating regime to become satisfactorily stable, it was decided to perform continuous data logging and to apply advanced post processing and analysis techniques. In this way, it was possible to preserve engine from excessive wear and obtain sufficiently accurate measuring.

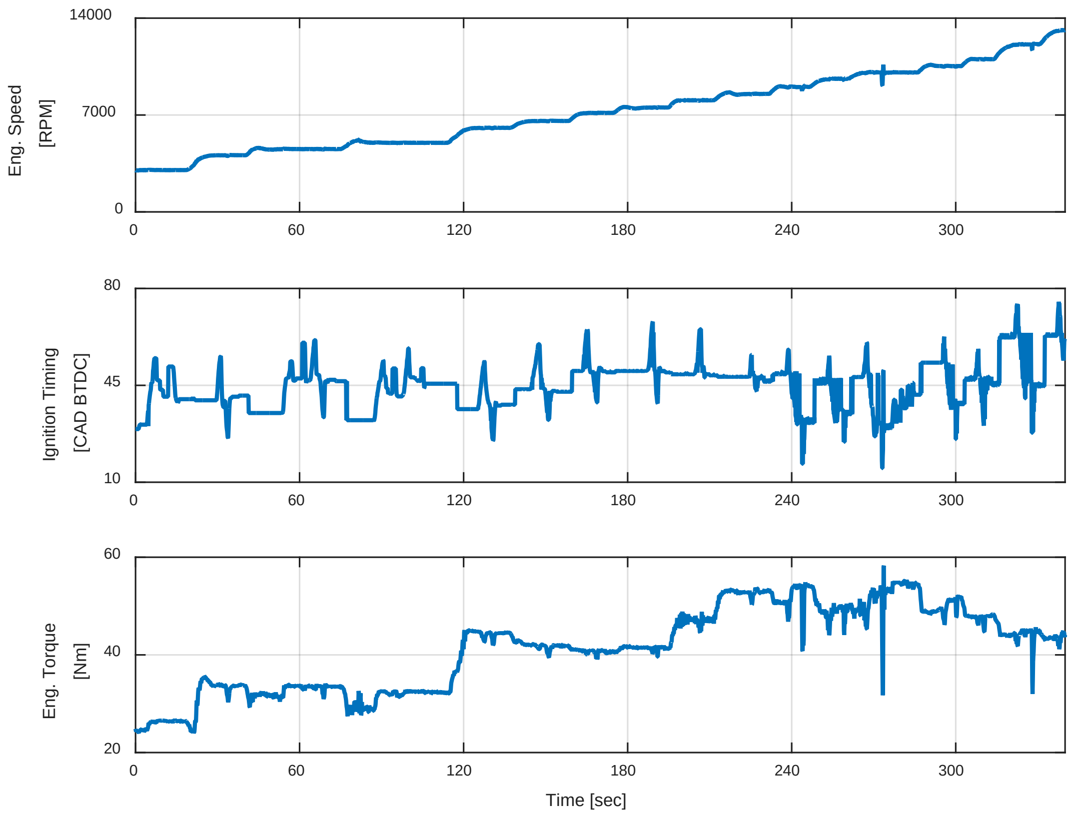

Figure 1. Engine speed, advance timing and engine torque change over the time during testing at WOT.

Data sets were acquired by the following test procedure:

- Engine load was increased slightly to the desired value of throttle opening (TPS and SPEED stops are defined by engine control maps). This was done for the whole range of TPS, from 0% to 100%. Dyno braking torque was increased simultaneously to prevent engine overrun;

– By adjusting dynamometer control parameters, desired engine SPEED was reached. Engine speed was varied from 3000 RPM up to 13500 RPM;
– For each pair of TPS and SPEED values, ignition advance timing (IGN) was varied in certain steps to achieve maximum brake torque;
– Injection duration (INJ) was automatically adjusted by the closed loop lambda controller in the way of obtaining predefined air to fuel equivalence ratio (AFR).

Acquired data sets were stored independently for each TPS value and for a whole range of SPEED. In the Fig. 1, change of engine speed, advance timing and engine brake torque is shown in the time domain for TPS=100%. Relatively small buffer moving average filter was applied along with predefined Savitzky-Golay [3] filter.

Because of continuous sampling, a large amount of data was obtained and additional post-processing needed to be applied to extract quasi-stationary testing data. The combination of IGN map tolerance filter coupled with sampling continuity data selection were applied to identify quasi-stationary results. In the Figure 2. are presented final selection of quasi-stationary values of engine torque and advance timings over the engine speed at WOT. All scripts for data analysis and post processing were made within MATLAB [4] with high level of modularity and automation.

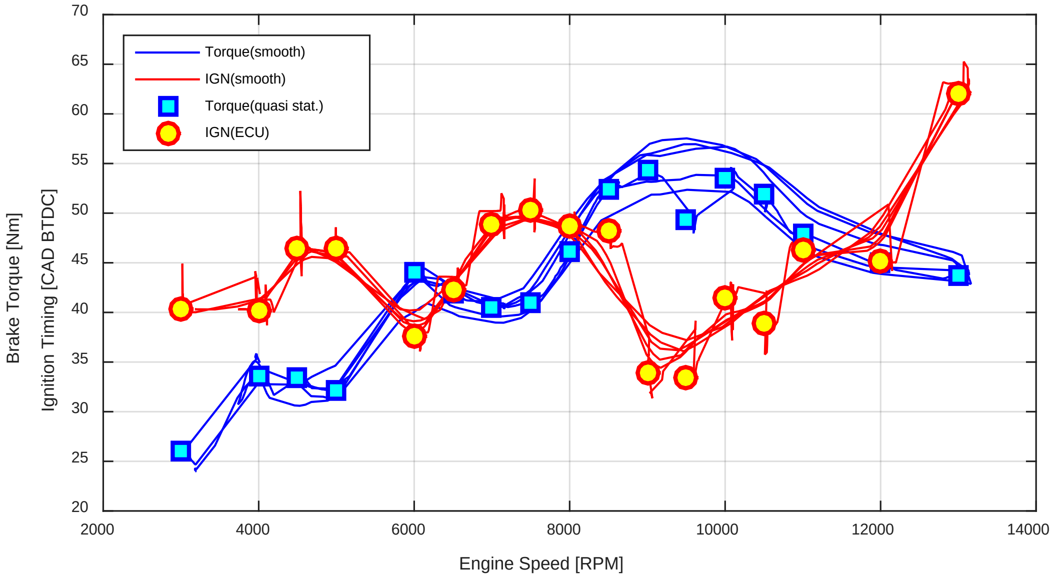

Figure 2. Data acquired during engine testing (dynamic examination with relatively small gradient of parameter change over the time) compared with quasi-stationary results.

From the results shown in the Fig.2. it is noted that advance timing is in direct correlation with engine volumetric efficiency (VE) change over the engine speed. Peaks on torque curve are also result of VE changes at constant TPS (and WOT) dictated by the effect of resonant charging, which was investigated by author [5].

5. Nonlinear dynamic process identification

As mentioned before, the idea of this paper is to take advantage of relatively large amount of recorded data with the aim to identify engine dynamic behavior within dynamic operating regimes. After formation of such a model (with a satisfactory error deviation), it is possible to investigate a model with stationary excitation which leads to stationary based engine calibration.

For such an approach the nonlinear autoregressive network with exogenous inputs (NARX) were formed [6]. It is a recurrent dynamic network with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX (Autoregressive with exogenous inputs) model, which is commonly used in time-series modeling. The concept of dynamic process modeling is formulated in the Equation 1.

$$\hat{y}(t)=f\left(\hat{y}_n(t-1),\hat{y}_n(t-2),...,\hat{y}_n(t-FD),u_m(t),u_m(t-1),u_m(t-2),...,u_m(t-ID)\right)$$
$$| \ n\in(0,...,N),\ m\in(0,...,M),t\in(0:ST:t_{max}) \tag{1}$$

Where listed variables represent:

$\hat{y}(t)$ – Mathematical model output at time sample t;

$u(t)$ – System excitation (input) at time sample t;

f – Link between system excitation and response within dynamic operation (NARX NN);

$(t-1)$ – Time delay argument. In the present case represents a previous time sample;

FD – Maximum number of feedback delays (recurrent input to the model $f(...)$);

ID – Maximum number of input delays;

n – Number of system outputs;

m – Number of system inputs.

In case analyzed for this paper, it is assumed that engine behavior combined with all of the processes taking place within it is a black-box model with two independent inputs (SPEED, IGN) and with one output (TORQUE) as shown on Figure 3. A-priori knowledge is taken into account during engine testing because IGN values at specific SPEED-TPS regime are conditioned by knock intensity.

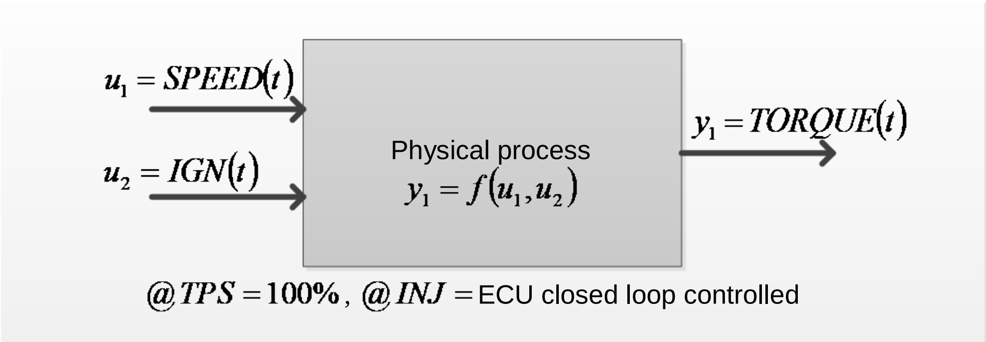

Figure 3. Physical process representation and introduced assumptions.

Data sets needed for NN training were prepared as a time series with ST of 0.1 second. This sample time is widely accepted for dynamic engine model examination. In addition, it is advised to train feedforward (FF) network in the first place, using backpropagation Levenberg-Marquardt training algorithm, and after successful FF validation to perform network model closing with the feedback (FB) line (output data).

Validation of the feedforward NN model, with time delays at the input side does not match with the results of the feedback NN model which is shown on the Fig. 4. In that reason, validation results of trained network could not be used for validation of the closed loop NARX model. In other words, for every generated network model it is required to perform a comparison between measured system response and results obtained by excitation of NN model with input data.

Second and the most important issue are setting of NN model parameters. A maximum number of feedback delays (FD) and input delays (ID) are unknown and those values need to be assumed in the way of getting the most accurate model response as possible. Also the number of hidden layers in the NN and number of neurons in each of the layers are unknown.

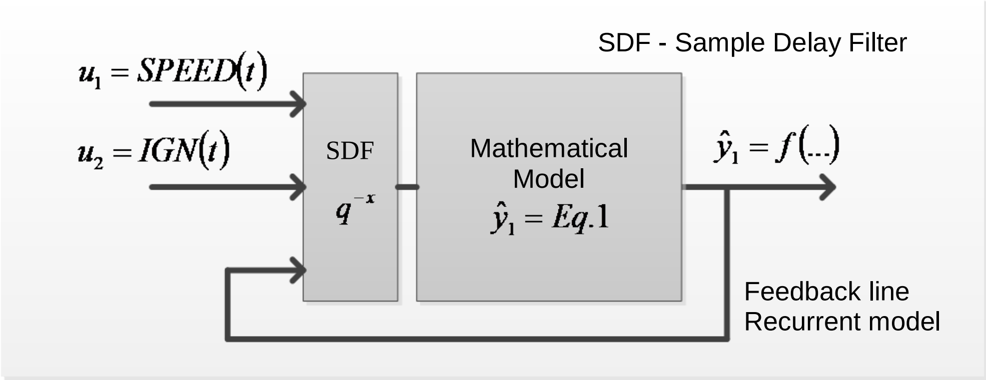

Figure 4. Schematic diagram of mathematical model (closed loop NARX NN).

Information about setting up the model parameter is rarely available in the literature. The main reason for that is a huge range of dynamic systems that could be modeled by NARX neural networks. Also, many scientific papers dealing with topic of engine calibration using this methodology handling with virtual lab results (results of engine 1D simulation), which greatly simplifies the problem due to lack of signal noise [7]. Very important question is related to proper system excitation [8] (in the amplitude and frequent domain) during recording of its response, but it is beyond the scope of this paper.

It was assumed that NN with two hidden layers will meet the criteria for sufficient accuracy of the model. Several full factorial NN training runs were performed to determine unknown NN parameters:

- 1. HLS (First Hidden Layer Size – HLS1)
- 2. HLS (Second Hidden Layer Size – HLS2)
- ID (Input Delay)
- FD (Feedback Delay)

In the Figure 5. are shown performances (Normalized Mean Square Errors - MSE) of FF and FB networks along with Sum of Squared Errors (SSE) between measured output (y) and closed loop NARX models output ($\hat{y}$) for different NN setups. It should be noted that presented results are local optimum in 4D setup parameters input space (four independent setup parameters of NN). In the last run NN setup parameters were varied in the following way:

- HLS1 = 1:1:3 (outer loop);
- HLS2 = 18:1:25;
- ID = 1:1:9;
- FD = 1:1:3 (inner loop), which leads to the creation and validation of 360 NN with different parameters setup.

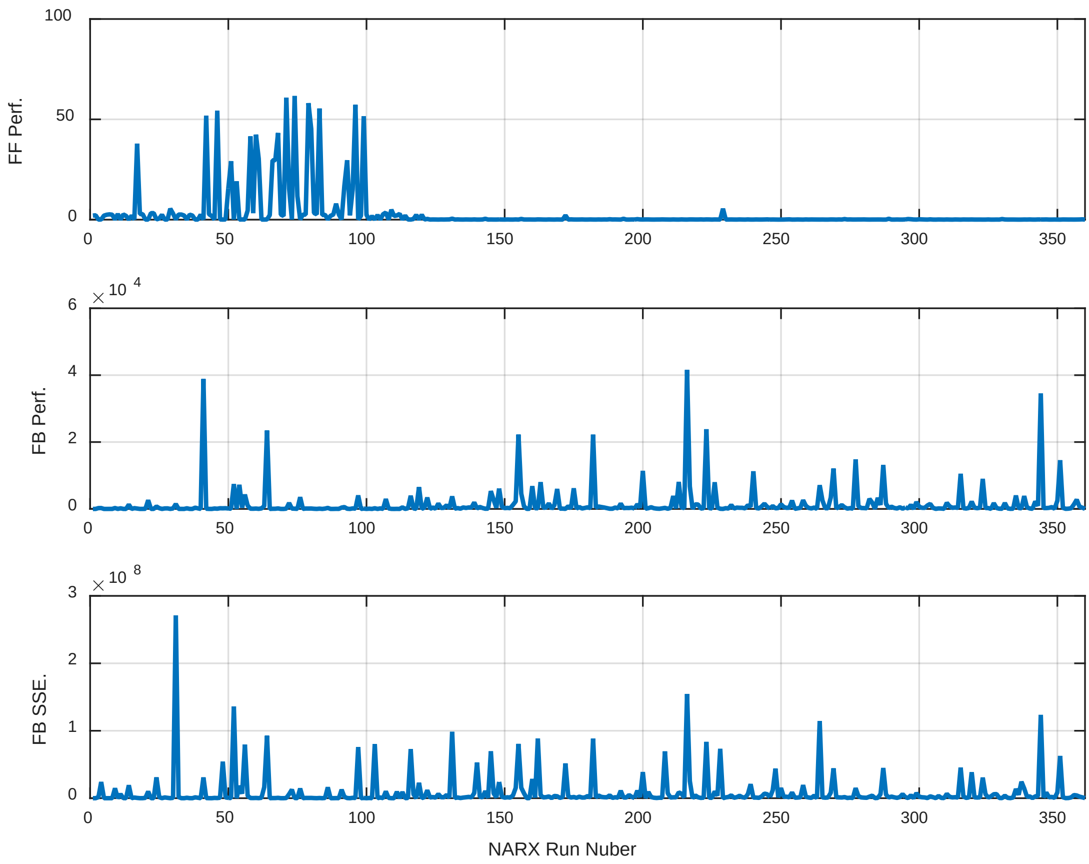

Figure 5. FF and FB NN performance and SSE between y and $\hat{y}$ for different NN setups.

The main problem in determining NN setup parameters is nonlinearity between setup parameters and the quality of the final (closed loop) model in terms of SSE. The combination of NN input parameters which leads to minimal SSE is selected and comparison of measured output (y) and modeled output ($\hat{y}$) are shown in the Figure 6.

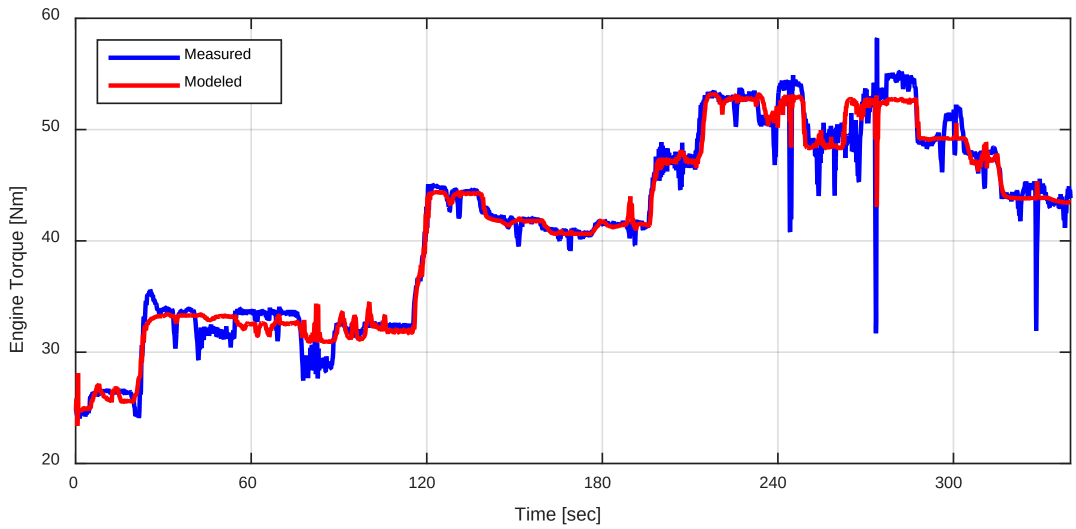

Figure 6. Comparison of measured engine torque during base engine calibration and modeled engine torque using the dynamic NARX model.

In this particular case, NN coefficients that behave dynamic system response in the best way are: HLS1 = 1, HLS2 = 21, ID = 8; FD = 1, and schematic diagrams of FF and FB networks are presented in the Figure 7.

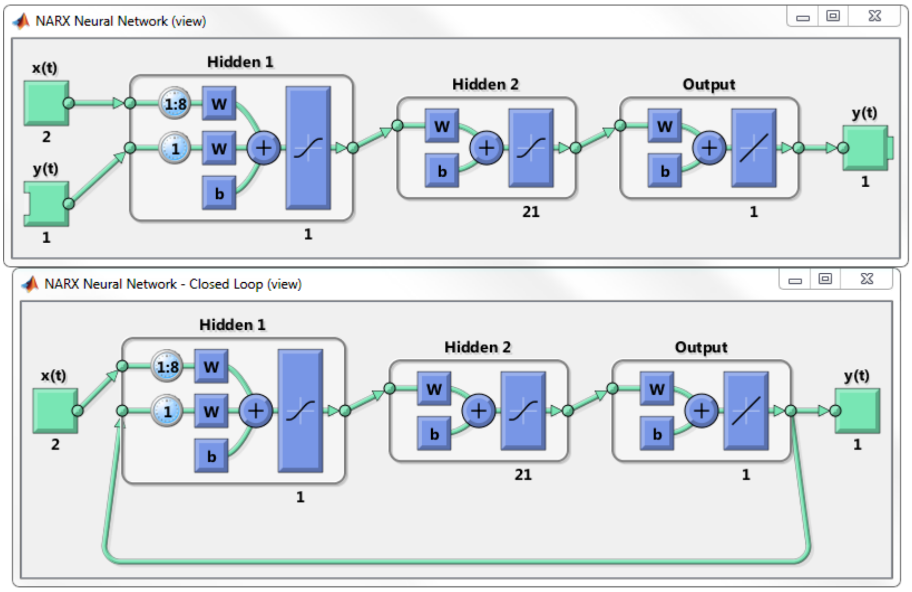

Figure 7. Feedforward NARX NN used for training (upper) and Feedback NN used for model validation (lower).

6. Stationary based engine calibration

The next step towards the formation of optimal lookup tables for stationary IGN is excitation of previously generated dynamic mathematical model of engine response. Due to the dynamic nature of the model, it is necessary to excite the model with stationary inputs in the time domain (time series of certain duration) due to the presence of model time response and stabilization phenomenon [9]. In this manner, the model was excited with stationary values of engine speeds and iteratively with stationary values of advance timing. As expected, the result should be stationary dependence of modeled engine torque as a function of engine speed and IGN timing. At this time, it should not be forgotten that IGN timing is a function of engine speed and load, so a-priori knowledge should be taken into account. In addition, in some regions (SPEED-IGN combinations) model does not have acceptable accuracy, but it could be overcome with model error analysis. In the Figure 8. is illustrated the process of stationary based model excitation.

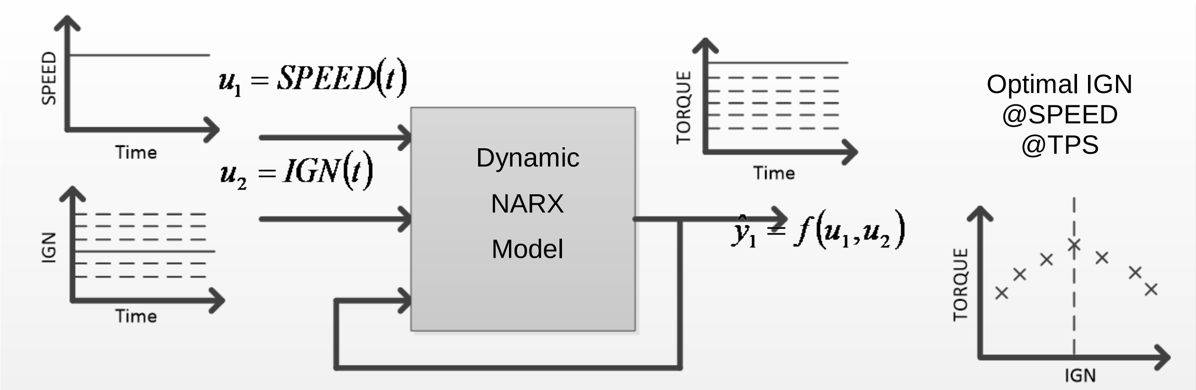

Figure 8. Process of stationary model excitation and formation of stationary dependency $\hat{y}_1 = f(u_1, u_2)$.

Limitations of IGN values are derived from experimental data presented in the Figure 1. Repeating the process of stationary excitation of the model, dependency of model output as a function of inputs was obtained ($\hat{y}_1 = f(u_1, u_2)$). Those results are shown in the Figure 9.

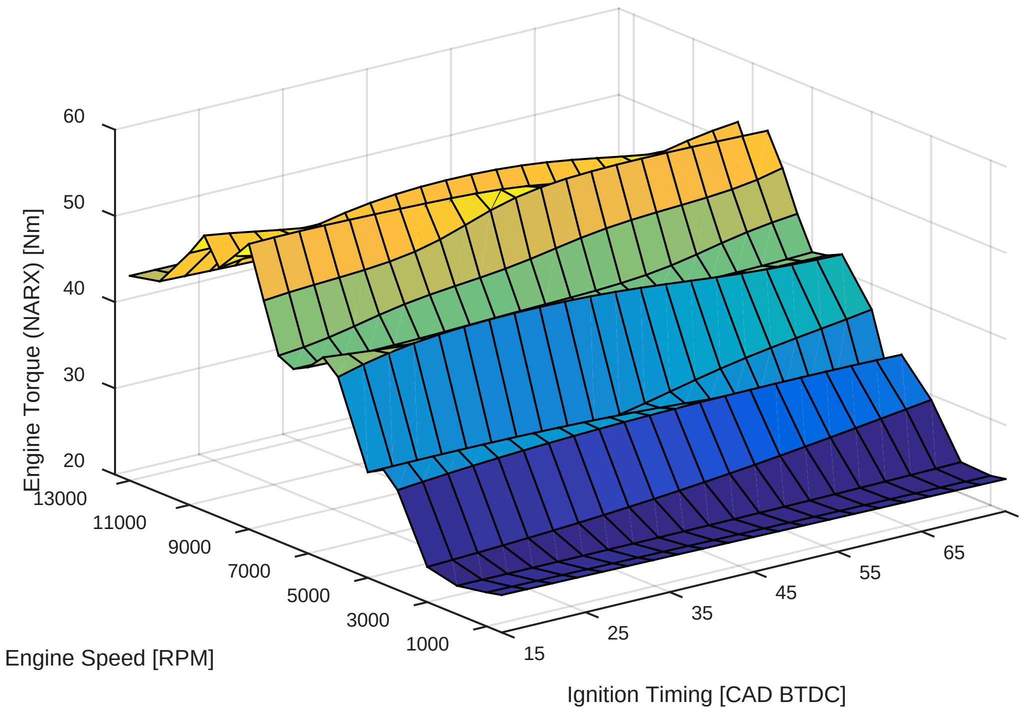

Figure 9. Stationary excitation of the model. Modeled engine torque as a function of engine speed and ignition timing at *WOT*.

Additionally, in the Figure 10. is presented comparison between measured and modeled engine torque as a function of engine speed at WOT for ignition timings from ECU lookup table (shown in the Figure 2.)

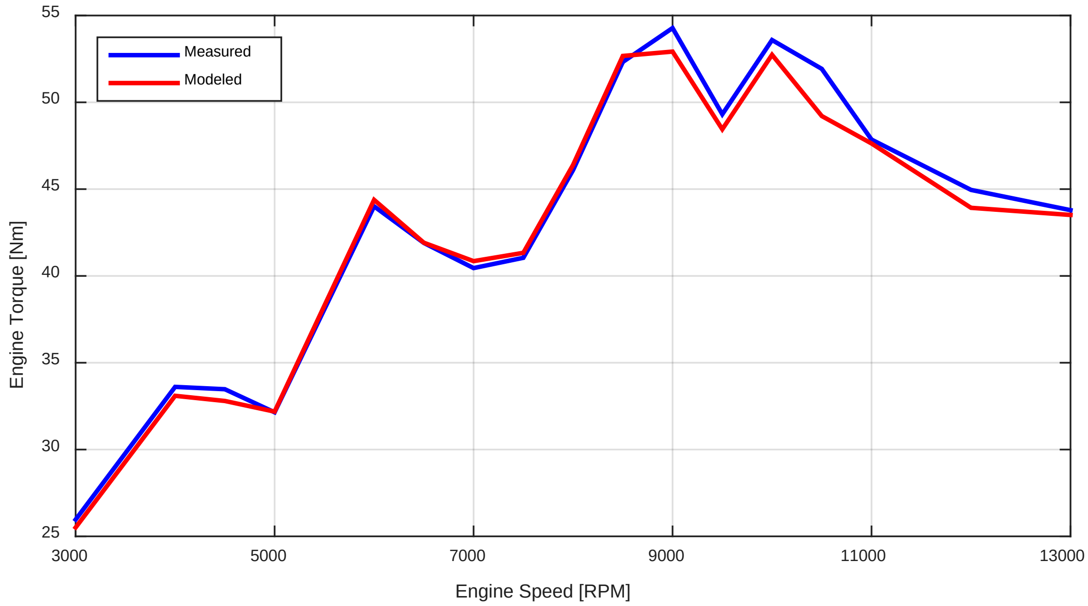

Figure 10. Comparison between measured and modeled stationary engine torque over the SPEED range at WOT and for IGN timing set in the ECU lookup table.

7. Conclusions

Evaluated mathematical model is very sensitive to initial NN setup parameters such as the number of hidden layers, number of neurons of every hidden layers, number of input delays and number of feedback delays. Also, sampling rate and configuration of filter properties are essential for good quality model. Beside Matlab toolboxes for nonlinear dynamic system identification, such as LMNtool [10], great attention will be given to implementation of AVL CAMEO [11] software because of features designed for powertrain development.

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