ABSTRACT

The aim of this thesis is the development of a complete framework for modeling and optimization for stationary base engine calibration. There already exist a lot of approaches and algorithms for this topic. However, in the literature the different methods are often examined separately and a comprehensive overview of all different methods does not exist until now. Hence, so far it is hard to determine which approaches are most suitable for stationary engine calibration. Therefore, one aspect of this work is the evaluation and comparison of the different methods, the other aspect is the improvement of these methods, wherever possible.

The proposed work can be listed as follows:-
1. Investigate the existing models
2. Enhance the models by including certain parameters which are not included as of now.
3. Validate the models with data tables available for various Engines.
4. Calibrate, optimize and revalidate

Keywords:- Automotive Engine calibration, modeling, optimization, Neural Networks

1. INTRODUCTION

Nowadays automotive manufacturers have to redesign their products more and more frequently to meet customers’ demands on innovation. The pressure of competitiveness is even higher for control system development, since more than 80% of innovation is in electronics. In today vehicles, the electronic control system is a networked system with more than 80 interconnected ECUs, some of them safety critical. At the same time exhaust emission laws are becoming very stringent day by day and the pressure on fuel economy has been increasing significantly in the last few years. In such a scenario, engine efficiency plays important role. For diesel engines, new technologies such as direct injection, multiple injection, variable valve train or Exhaust Gas Recirculation (EGR) are towards improving fuel economy and to reduce emissions in the exhaust. Such technologies lead to high degree of freedom systems. The Engine management system has to handle this increased complexity. The traditional look up tables will increase exponentially as the degrees of freedom increase which will in turn lead to the increase of complexity and cost of mapping and calibration. The memory consumption of ECU (Electronic control Unit) will increase substantially. In order to reduce air pollution, governments around the world introduced emission standards. An example is the European emission standards (EURO standards), which was introduced in the EU member states. Two important quantities of the EURO standards, the particulate matter and the sum of HC and NOx emissions of a diesel engine for passenger cars, are shown in Figure 1.1.
1.1 Engine
The internal combustion engine is an engine in which the combustion of a fuel (normally made up of hydrocarbons derived from fossil fuels) occurs with an oxidizer (usually oxygen in air) in a combustion chamber that is an integral part of the working fluid flow circuit. In an internal combustion engine (ICE) the expansion of the high-temperature and high-pressure gases produced by combustion apply direct force to some component of the engine. The force is applied typically to pistons, turbine blades, or a nozzle. This force moves the component over a distance, transforming chemical energy into useful mechanical energy. Engines can be classified in many different ways: By the engine cycle used, the layout of the engine, source of energy, the use of the engine, or by the cooling system employed. Common layouts of engines are: Under Reciprocating: Two-stroke engine, Four-stroke engine (Otto cycle), Six-stroke engine, Diesel engine, Atkinson cycle, Miller cycle; Under Rotary: Wankel engine; Under Continuous combustion: Gas turbine, Jet engine (including turbojet, turbofan, ramjet, Rocket, etc.).

Some of the main inputs/outputs of the engine are as shown in Figure 1.2 [22].

![Figure 1.2: Engine Input/Output’s](image)

1.2 Engine Control Unit and its calibration
Automotive System can be depicted as a closed loop control system as shown in Figure 1.3.

![Figure 1.3: Automotive System as a control system](image)

In general, in control system design, variables such as exhaust temperature, exhaust manifold pressure are the usual feedback signals. BSFC (Break Specific Fuel Consumption) and concentration or specific emissions are the objective variables to which controller set points are set in order to achieve minimum values. All of these variables can potentially be represented by black box models. In the automotive industry, Engine Control Unit (ECU) calibration is the process of determining the optimal calibration tables for an engine [12]. This multistep process involves designing tests, collecting data, analyzing the data, and calibrating lookup tables to model the engine. This process helps to identify the optimal balance of engine performance, emissions, and fuel economy. You can also use models developed during ECU calibration for control design, hardware-in-the-loop (HIL) testing [2], or power train simulation. The Air to Fuel ratio should be 14.7:1 for gasoline based vehicles and 14.5:1 for diesel vehicles, which is known as Stoichiometric ratio for very low emissions. The chemical formula is HC + O2 = H2O + CO2 i.e., Hydrocarbons (Fuel) + Oxygen (Air) = Water + Carbon dioxide. Water and Carbon dioxide are harmless to the atmosphere. If the Air Fuel ratio is not proper, the combustion process will not be proper. Less air will lead to un-burnt Hydrocarbons and Carbon Monoxide (CO). More Air in very high temperatures will lead to Nox (Oxides of Nitrogen) due to combining of oxygen with Nitrogen in air. Optimum calibration is very much necessary for the reduced emissions. In general calibration can be divided into two parts such as Stationary calibration and Vehicle calibration. The Stationary calibration is performed with reference to Engine Control Unit (ECU). The structure of calibration is shown in Figure 1.4 [22].
1.3 Recent Trends in Engine calibration
In recent years, engine calibration efforts have increased dramatically in order to fulfill legislation requirements, in particular the reduction of undesired emissions and fuel consumption while maintaining drivability and meeting comfort demands. Dynamic modeling has been shown to be a useful tool in this context. Artificial Neural Network (ANN) provides a broad spectrum of functions which are required in the field of engine applications such as modeling, onboard testing and diagnostics [8]. Use of non-linear functions in neural networks is offering one important route to managing the data tables with high speed (i.e. reduction of response time) and accuracy (precision) in comparison to existing conventional simulator during calibration and testing of ECU in the development process. Recently studies are going on for “Real-Time Self-Learning Optimization of Diesel Engine Calibration”. “For an engine with a given technology, what are the optimum performance criteria that a driver can get with respect to his/her driving habits?” The long-term potential benefits of this approach are substantial. True fuel economy of vehicles will be increased while meeting emission standard regulations; drivers will be able to evaluate their driving behaviour and learn how to improve fuel economy and reduce emissions by modifying it. [3]

2. OPTIMIZATION OF ENGINE CALIBRATION
Broadly the optimization is categorized into Measurement based optimization and Model based optimization.

2.1 Measurement-Based Optimization
If only a few parameters should be optimized (2-3 parameters), then the parameter space is low-dimensional and measurement-based optimization can be used. This approach has many advantages. The techniques are simple to implement and easy to understand. Therefore, the engineer needs no special knowledge and can interpret the results very fast. However, as we will see soon, due to the curse of dimensionality these approaches cannot be used for an optimization with many parameters. Since the number of parameters increased rapidly in the last years, as said above, nowadays measurement-based optimization is only used for special problems. Therefore, this thesis focuses rather on model-based optimization.

2.2 Model-Based Optimization
Two different approaches for model-based optimization, such as offline optimization and online optimization, can be distinguished.

2.2.1 Model-Based Offline Optimization
The model-based offline optimization is characterized by strict separation between the measurements on the test bench and the modeling on the PC. Figure 2.1 shows a schematic diagram of this method [22]. In an initial step, an experimental design is planned. Various different techniques have been developed and used for this task. After taking measurements on the test bench, a modeling of the desired parameters is performed. With these models, the optimal settings of the parameters can be found by numerical optimization. Afterwards, these optimal values are verified on the test bench. If the verification was successful, then the engine operation maps are generated and stored on the ECU. A serious drawback of this approach is that the quality of the models is not checked during the measurements on the test bench. If the model quality is bad, e.g. if too few measurements are performed or too many outliers occur in the data, then the prediction of the optimal values will be wrong. Thus, the verification will fail and the optimization has to be started over again. This drawback can be overcome with the model-based online optimization.
2.2.2 Model-Based Online Optimization

In the last few years, there is a trend to model-based online optimization, where measurement, modeling, and optimization are not strictly separated. Hence, the modeling and optimization algorithms are in a permanent interaction with the test bench, which allows the models to give a feedback of their quality. This has various advantages. First, the modeling can give a feedback if already enough measurements are taken and the measurement on the test bench can be stopped. Hence, the test bench time can be reduced to an optimal amount. Second, the models can provide information in which areas the measurements should be taken in order to achieve the maximum of information. Thus, the test bench time can be used more efficiently. Hence, time and costs on the test bed can be considerably reduced by the usage of model-based online optimization.

The scheme of Model-based online optimization is as shown in Figure 2.2 [22].

2.3 Stationary and Dynamic Modeling

For measurement data acquisition and modeling, stationary and dynamic approaches have been developed and used for offline and online optimization in engine calibration. Many calibration tasks are performed stationary, and therefore the measurement is often performed stationary. Depending on the dynamic of the considered measurement variables and on the noise on the measurements, the time for a single stationary measurement can add up to a few minutes. In order to avoid this time-intensive procedure, in recent years several non-stationary measurement techniques have been developed. Some of them are intended for a stationary modeling, like Sweeping and Slow Dynamic Slope. In these approaches, the measurements are performed in a way such that the dynamic behavior of the system is suppressed and the stationary values can be calculated. Nowadays in base calibration the adjustment parameters are typically optimized on the stationary state of the engine. In addition, until now many other functions on the ECU are only realized as stationary functions and in many cases optimization of the transient state is not possible. Therefore, a stationary modeling is most commonly used in engine calibration. A dynamic modeling has two advantages. First, a dynamic measurement can be used, which allows to save a considerable amount of time compared to a stationary measurement. Second, the dynamic behavior of the engine can be represented. Since e.g. a lot of emissions are generated in the transient states of the engine, a dynamic optimization of these states could be a great improvement, if the results of this optimization could be considered in future versions of the ECU. Hence, the dynamic modeling gained a lot of interest in recent years and a lot of research has been made. Some of the modeling approaches are MLP (Multilayer Perceptron) Neural Network [16], RBF (Radial Basis Function) Neural Network [15], Gaussian Process [7], Polynomial step-wise
regression [15]. Non linear Regression. Some of the dynamic models act as the basic for a fuel path control system, neural network approach to represent air flow rate [10], NOx prediction neural network model [9] and Smoke prediction neural network model [5]. The challenges that are to be met in modern combustion engines are real time operation and the mapping of complex non-linear and dynamic patterns in Engine behavior. There is NLARX (Non Linear Auto Regressive exogenous input) neural network [5] to represent intake manifold pressure, exhaust manifold temperature, exhaust manifold pressure to support control system development. They can accommodate dynamics of the system feeding previous network outputs back into the input layer. It also enables the user to define how many previous output and input time steps are required for representing the systems dynamics best. The automotive sector has applied neural network models in several different cases. Their main implementation is seen in control design in the area of engine operation. Hence, in Engine development neural networks are used for applications such as fuel injection, output performance or speed. Additionally, variable turbine geometry (VGT), Exhaust gas recirculation (EGR) [9] or variable valve timing (VVT) [20], have been modeled using ANN. It is also used for virtual sensing such as emissions [14], misfire detection, torque monitoring [13] or tire pressure change detection. AFR has also been modeled [10] [11] [13] [21]. According to a few experiments conducted, fuzzy logic approach has more predictive ability than ANN [1]. These experiments were conducted for predictions of a diesel engine performance of Brake Mean Effective Pressure (BMEP), Fuel Flow (FF), Specific Fuel Consumption (SFC).

3. REQUIREMENTS OF MODELING

1. The modeling must be suitable for high-dimensional problems (5-10 input dimensions). The term ‘high-dimensional’ refers to the application of engine calibration. In the machine learning area, a high-dimensional problem would regard a few hundred inputs. A practical example in engine calibration is the optimization of a diesel engine with six parameters: quantity and time of the pre-injection, quantity and time of the post-injection, main injection time and injection pressure. This leads to a six dimensional input space.

2. The engine test bench is an expensive system. Hence, the number of measurements should be minimized, in order to reduce time and costs of the calibration. Therefore, the modeling should be able to achieve a good performance with as few measurements as possible. That is why every measurement should contribute a maximum of information to the model.

3. The modeling should be flexible enough, so that every nonlinear engine mapping can be approximated. A good adaptation of the model to the measurement data should always be possible.

4. The algorithm should be able to determine the optimal flexibility of the model and the problem of over-fitting has to be solved. The model-flexibility must never be too big, and an over-fitting on the measurement data has to be avoided. Thus, the modeling has to be robust to noise on the measurements.

5. The requirements (3) and (4) above have to be met every time the modeling is performed. In addition, these tasks have to be performed automatically and dependably, so that an automated online optimization with no manual interaction is possible. This requirement is crucial. If, at any time, the modeling is not able to be flexible enough or over-fitting occurs, in an automated online optimization bad models will lead to wrong predictions and useless measurements will be taken at undesired regions. In the worst case, without manual interaction, a large part of measurements would be meaningless and the optimization would cause high costs.

6. In the model-based online optimization we want to take measurements in areas where the model quality is bad, in order to improve the prediction of the model. Hence, the modeling has not only to be able to predict an expectation about the true engine behaviour, but also a quantity about the certainty and probability of the model is important for an automated online optimization. Only with this quantity, measurement points cannot only be placed at the assumed optimum, but also where a big uncertainty about the model-expectation occurs.

3.1 Comparison of various approaches of Modeling and Optimization

The comparison of various approaches of Modeling and Optimization are discussed in the sub-sections to follow.

3.1.1 Comparison of approaches of optimization

The comparison of various approaches of optimization is provided in the Table 3.1.
3.1.2 Comparison of various approaches of Modeling

The comparison of various approaches of modeling is provided in the Table 3.2.

Table 3.2: Comparison table for various approaches of Modeling

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Modeling Approaches</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Polynomial step-wise regression – suitable for Linear models</td>
<td>Simple, easy, cheap.</td>
<td>1. Bad extrapolation of data tends very fast to high values outside the region of measurement data. 2. High order tends to variability and end effects oscillation at the edges of the interval. 3. Has problems in approximation this function.</td>
</tr>
<tr>
<td>2</td>
<td>Gaussian Process (GP) [17]</td>
<td>Performs much better compared to local linear modeling and polynomials, when it comes to practical data. 2. Gaussian process provide a principled, practical, probabilistic approach to learning in kernel machines. This gives advantages with respect to the interpretation of model predictions and provides a well-founded framework for learning and model selection. Theoretical and practical developments of over the last decade have made Gaussian processes a serious competitor for real supervised learning applications.</td>
<td>1. SE Kernel (Gauss processes) tends to mean of the data, if every measurement is far away from the prediction. 2. The computational cost of Gaussian processes is relatively high, when compared to the other types of modeling.</td>
</tr>
<tr>
<td>3</td>
<td>RBF (Radial Basis Function) Network is an Artificial Neural Network.</td>
<td>RBF models are good at approximation of local properties.</td>
<td>They cannot adapt the global behavior well.</td>
</tr>
<tr>
<td>4</td>
<td>LLR (Local Linear Model) is a combination of polynomial and RBF. The combination is obtained by Gaussian process.</td>
<td>It is argued that a polynomial model is able to approximate the global behavior of a function.</td>
<td>Difficulties arise when it comes to adaptation of local behavior.</td>
</tr>
</tbody>
</table>
### Modeling Parameters

Various modeling parameters have been listed in Table 3.3.

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Key Characteristics</th>
<th>Drawbacks/Notes</th>
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</table>
| LOLIMOT             | 1. The architecture supports both feed-forward and learning phase computations with reconfigurable processing engines.  
                      | 2. The architecture supports matrix inversion, multiplication and matrix power.  
                      | 3. Some of the main advantages of the LOLIMOT approach is its fast training time of some 10-30s, compared to many minutes to hours with other neural networks. Its applicability to adaptive problems (Fischer et al., 1998) and the interpretability of the net structure and parameters in a physical sense. | The drawbacks are that only orthogonal cuts are performed and that the local estimation approach may lead to interpolation errors. |
| HHT                 | 1. Using hinge hyper planes in a binary tree structure, the obtained model remains still interpretable.  
                      | 2. In comparison to LOLIMOT, the HHT (hinging hyper plane tree) algorithm allows also intersections, which are not axis orthogonal. This is achieved by using a nonlinear optimization, in order to obtain the optimal directions of the straight intersections. | The drawback is of course that decisions used as ground truth cannot be used to improve the performance of the system. |
| MLP                 | 1. Can be trained on new data as it becomes available  
                      | 2. Will track changes in the data set                                                   | Usage of multi layer perceptrons (MLP) with error back propagation learning algorithm has some disadvantages, most of them are complexity or even impossibility to relearn, slow training and orientation on supervised learning. |
| SVM                 | Support vector machines have been one of the major kernel methods for data classification. | SVM has various disadvantages compared to GP.                                      |
| ARMA                | ARMA modeling proceeds by a series of well-defined steps.                             | ARMA models are not able to handle time series that are not stationary in mean and variance. In other words, ARMA models should only be fitted to time series that are stationary in mean (i.e. no trend or no seasonal pattern) and stationary in variance. |
| Kalman Filters      | Advantages are similar to Gaussian process.                                           | Disadvantages are similar to Gaussian process.                                    |
| Local Neuro Fuzzy Models | Compared with the two other methods such as LOLIMOT and HHT, this algorithm has the greatest flexibility. | It is also the one with the highest computational costs. |

3.2 Modeling Parameters

Various modeling parameters have been listed in Table 3.3.
Table 3.3: Modeling parameters

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<tbody>
<tr>
<td>Modeling compression ratio</td>
<td>Brakes Thermal Efficiency (BTE)</td>
<td>Brake Power (BF)</td>
<td>engine speed</td>
<td>NOx emissions of a Diesel engine</td>
<td>injection pressure</td>
<td>intake manifold pressure</td>
</tr>
<tr>
<td>Injection timing</td>
<td>Brakes Specific Energy Consumption (BSEC)</td>
<td>Brake Thermal Efficiency (BTE)</td>
<td>engine load</td>
<td>Adaptive Feedforward Control of Ignition Angle</td>
<td>engine speed</td>
<td>exhaust manifold temperature</td>
</tr>
<tr>
<td>Injection pressure</td>
<td>Exhaust gas temperature</td>
<td>Brakes Specific Fuel Consumption (BSFC)</td>
<td>start of injection</td>
<td>Cylinder Pressure</td>
<td>throttle positions</td>
<td>exhaust manifold pressure</td>
</tr>
<tr>
<td>Air Fuel Ratio</td>
<td>Engine emissions</td>
<td>Volumetric efficiency</td>
<td>injection pressure</td>
<td>engine speed</td>
<td>torque values</td>
<td>exhaust manifold pressure</td>
</tr>
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</table>

4. CONCLUSION

Automotive is certainly one of the most attractive and promising application domains for Neural Network techniques. However, despite the significant advances achieved in the past few years, Neural Networks have not been effectively introduced in the automotive industry design processes at large. The European Commission intends to introduce a new regulation in 2017 called Euro 6c with the introduction of Real Driving Emissions tests for new Diesel Vehicle homologation. This novel test will add new constraints due to very fast transient conditions and thus requires new tools & methodologies to optimize the injection input parameters. The conventional calibration technique using the DoE (Design of Experiments) method on engine test bed gives a good initial engine setting but does not allow for optimization during dynamic operation. The objective of this research project is to enhance the already existing mathematical and neural network based approaches in order to prepare the development of future passenger cars.

REFERENCES

[4] Arsie, I., Di Iorio, S., Pianese, C., Rizzo, G., Sorrentino, M. Department of Mechanical Engineering, University of Salerno Fisciano, 84084, Italy; Recurrent Neural networks for Air fuel ratio estimation and control in spark-ignited engines; 2008 IFAC.
[6] Benjamin Berger, Florian Rauscher and Boris Lohmann; Analyzing Gaussian processes for stationary Black box combustion Engine modeling 18th IFAC World Congress August 28-September 2, 2011
[8] Bernardini, A; Asensio, J; Olazagoitia, J.L.; Biera, J. ; Optimal neural network for automotive products development; Mathworks Automotive conference 2010, 22-23 June 2010 Stuttgart, Germany
[16] Michael Deflorian, Florian Klopp, Joachim Ruckert; Online Dynamic Black box modeling and adaptive experiment design in combustion Engine calibration, BMW group, Minhcn, D-80788, Germany, IFAC 2010
[18] Rolf Isermann and Norbert Muller; Darmstadt University of Technology, Institute of Automatic Control Laboratory of Control Systems and Process Automation, Landgraf-Georg-Str.4, D-64283 Darmstadt, Germany; Modeling and adaptive control of combustion engines with fast neural networks

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