Rail Pressure Estimation for Fault Diagnosis in High Pressure Fuel Supply and Injection System

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Abstract: *Engine roughness* (ER) is a complex issue in GDI engines and a frequent customer complaint in workshops. Still it is hard to isolate the root cause of the vibration which is received by the driver. The present paper aims to identify the type and extent of faults causing ER that have their origin in the fuel supply and injection system. The method is presented using the injectors as an example, since they have a great impact on engine related vibrations.
The injectors affect ER through mixture formation. For example, a deviating amount of injected fuel mass on one cylinder leads to a deviating delivery of work during the combustion cycle and thus causes vibrations.
For the investigation additional pressure sensors were installed in the high pressure fuel system to observe the transfer behavior in the hydraulic system. Tests were executed in different reference and fault states, where a fault state is represented by deviating mass flows of an injector. The generated data is used to develop a parameter estimation model, describing the pressure in the fuel rail of the investigated engine.
Firstly, a set of *reference parameters* is generated by a parameter optimization algorithm for each operating point under reference conditions. Then, these sets of parameters are used for initial calibration of the model for the following injector diagnosis. Observing the adaptation of a separate set of *diagnostic parameters*, allows for a precise pinpointing to a defective injector. It also delivers information about the type of fault and its size. Finally, the results are reconfirmed by executing the diagnosis on data of a healthy system to preclude mis-detections of faults.

Keywords: Diagnosis, Model based recognition, Parameter optimization, Parameter estimation, Injection system, Internal combustion engines, Prediction methods

1. INTRODUCTION

Engine Roughness (ER) is a known phenomenon of spark ignition engines. In many cases faults leading to noticeable ER are not big enough to be detected by law driven on board diagnostics (OBD) CARB [2015] and CARB [2016]. Consequently no entry in the fault memory is available for the technician in the workshop with which he can identify the root cause of the customer's complaint. As modern combustion engines are highly complex powertrains with a vast amount of sensors, actuators, communication systems and even hybrid powertrain components, workshop tester systems have been introduced to help technicians choose the right repair action. A number of automated tests is executed on the vehicle in the workshop to create symptoms, which lead the technician to a reliable diagnosis. Still it is essential to collect as many diagnostic results as possible onboard, as not all operating points in which the fault occurs can be reproduced in the workshop.
Three seperate processes control the combustion of a gasoline engine: the inlet and exhaust path including gas exchange, the ignition system, and the fuel supply system. As the injected fuel mass into a cylinder is decisive for cylinder pressure progression, degrading injectors have a direct impact on the vibration behavior of an engine. Thus the fuel system of a four cylinder gasoline engine, presented in Figure 2, is investigated to find faulty injectors.
During a subject study in Hartl et al. [2018], a sensation threshold for vibrations in a car was introduced. It was determined for an average driver to an excitation level corresponding to 25% lean out of a single cylinder. Consequently, to be able to identify and monitor the fault before the customer realizes ER the method has to detect fuel mass deviations before reaching the sensation threshold. To do so, a model of the pressure progression in the fuel rail has to be developed. By comparing the model output with the measured signal, one can draw a conclusion on a specific fault. Therefore, change detection in the model parameters must be precise enough to meet the requirements.
Several research approaches on diagnosing a high pressure fuel system have been conducted. In Kimmich [2002], a

model-based attempt for diagnosing deviations in injection mass of a diesel engine was tested using O_2 measurement in the exhaust gas path downstream the turbine. Regarding the amount of linearized models used for this attempt, the method has very high requirements for operating conditions to be able to detect faults. A hydraulic model for fault-detection related to the High Pressure Pump (HPP) of the fuel system was tested in Leykauf [2008]. As this attempt is restricted to faults in the HPP, it is not sufficient for injector diagnosis. A possibility for detection of faulty injectors based on Wavelet Analysis is presented in Isermann [2017]. The outcome is a method, which is capable of detecting faults in the high pressure fuel system but not to localize or quantify it.
The objective of the present investigation is to develop a method, which allows to detect faults in the fuel system and to identify its type and extent. The method is developed through the analysis of deviating mass flows in the injector.

2. SELECTION OF AN IDENTIFICATION STRATEGY

In Bohn [2015] different identification methods and modeling strategies for diagnostics are described. In the following a parameter estimation approach is chosen to detect changes in the process of fuel injection. As Figure 1 shows, a process model uses actuator information from the injectors as input and reproduces the output of the process. The modeled pressure progression $p_{modeled}$ is compared to the measured pressure p_{meas} to create diagnostic features and an analytical redundancy to identify deviations in the process, compare Isermann [2017].
Methods based on process models typically consist of a

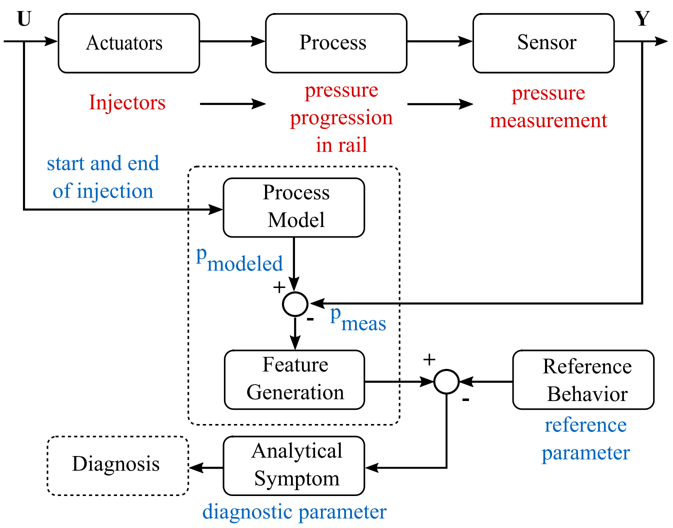

Fig. 1. Process model based fault detection: Actuator information is used for symptom generation

mathematical structure and process parameters for model tuning. While the mathematical structure is mainly defined by differential equations, which describe the physical behavior of the system, the process parameters are often unknown. If this is the case, the process parameters have to be estimated recursively to follow the system's behavior. Basically, the parameters are determined in a way, that a previously defined output-error is minimized. Here the residual Δp between $p_{modeled}$ and p_{meas} has to be considered in each optimization sequence. Based on the type of fault and the required accuracy, the output-error Δp is weighted with empirical exponents and an abort criterion for the optimization is defined. Therefore, an iterative, numerical parameter optimizer is used. If a change in process parameters is observed during process execution, a change in operating conditions will be detected. By evaluating the pattern of parameter changes, the current fault can be identified regarding its location, type and extent.
The presented model uses the timings of actuation of the flow control valve (FCV), of the HPP, and the injectors in combination with their characteristic curves of dynamic volume flow. The calculation of differences in fuel volume ΔV is evaluated to differences in fuel pressure Δp using the control volume V_{Rail} and the coefficient of comprssibility K in the equation of compressibility:

$$\Delta p = \frac{K}{V_{Rail}} \cdot \Delta V \tag{1}$$

3. DATA GENERATION

To get a better comprehension of the pressure oscillation behavior inside the control volume of the fuel rail at different operating points of the engine, a measurement program is conducted. The aim is to understand the influence of the actuation timings on the pressure progression. The generated knowledge is used to define the architecture of the parameter estimator.

3.1 Additional Measurement Points

Figure 2 shows how additional sensors are installed near each of the injectors (Sens 3-6), near the HPP (Sens 1), and near the original fuel rail pressure sensor (Sens 2). The additional sensors allow a sampling rate of 5kHz, which ensures to have at least 400 sampling points during a combustion cycle (CC) for all relevant operating points.

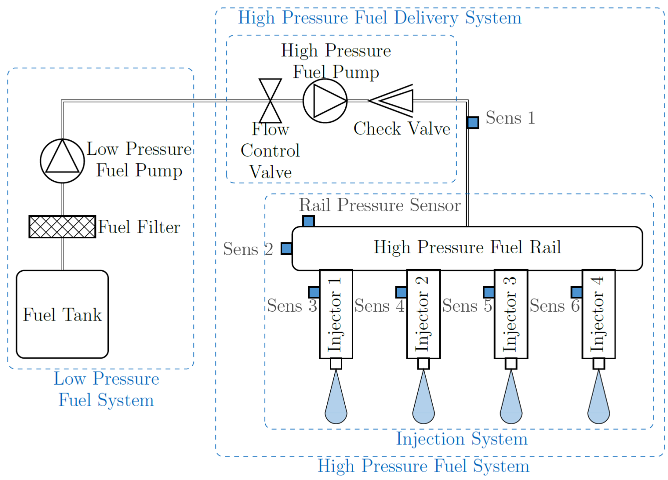

Fig. 2. Schematic of the fuel system with additional sensors (Sens i with $i = 1, \ldots, 6$).

3.2 Simulated Faults

To simulate failing injectors, injectors of the same type but with different stationary mass flow are installed in the vehicle. Next to the standard injectors two sets of injectors with a 32% and a 59% higher mass flow are available for the experiments. Using different combinations of the sets, a leaking injector, as well as a sooted injector is reproducible, each in two grades of intensity.

3.3 Design of Experiment

Every fault is tested at engine operating points of 60km/h and 100km/h of steady state driving. Since the fuel pressure oscillations are hardly affected by transient operation points the developed method is not restricted to stationarity. To ensure reproducibility of the basic conditions for the experiments, only stationary operating points are considered during the experiments.

4. DATA ANALYSIS

4.1 Signal Preprocessing

After measurement data is imported, it is scanned for stationary operating points. These are examined separately for a focused analysis. Preprocessing, like converting time series data to degrees of crankangle (°CA) and CC, as well as calculation of actuation timings like Start of Injection (SOI) and end of injection (EOI) for the injectors must be conducted before being able to interpret the signal progression of the pressure sensors.
For the purpose of easier modeling, the signals of the additional pressure sensors are filtered using an FIR filter with a passband frequency corresponding to the 60th engine order. For data analysis, only unfiltered signals are considered to see all the characteristics of the signal progression.

4.2 Results of Signal Analysis

In order to be able to model the pressure signal, five aspects turned out to be important for the model accuracy during the data analysis (the order of the bullet points gives no priorization):

- The general signal shape,
- The temporal relation between an actuation and the observable reaction of the system on the corresponding actuator-near sensor signal,
- The temporal relation between the signal progression of an actuator-near sensor signal and the rail pressure sensor,
- The damping characteristic of gasoline within the fuel rail geometry regarding the filtering effect on pressure peaks,
- The influence of high frequency oscillations.

Figure 3 illustrates the shape of the fuel rail pressure signal over one CC. The vertical lines indicate the beginnings and endings of an injection, as well as the closings and openings of the FCV.

The deviation in timing between the actuation of an injector and the pressure signal of the corresponding sensor is depicted in Figure 4. The pressure drop begins, before the ECU setpoint actively initiates the injection. This is caused by a blackbox closed-loop controller inside the ECU, which optimizes each single injection timing. For the timing of the FCV, a check valve on the high pressure side of the HPP causes delays in pressure build-up.
Figure 5 shows the transition behavior between two differently located sensors. The solid graph depicts the measured pressure at the rail pressure sensor, the dashed line indicates the signal progression of the sensor near the injector of cylinder 1. This injector is the closest to the rail pressure sensor. Right next to the injector, the oscillations of the fuel pressure are much higher than at the rail pressure sensor but without a relevant time delay between

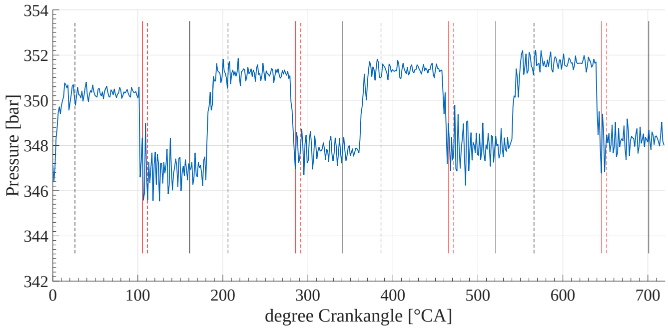

Fig. 3. Fuel pressure progression during one CC (reference state). The vertical lines show start (solid line) and end of actuations (dashed line) for pump strokes (black) and injections (red)

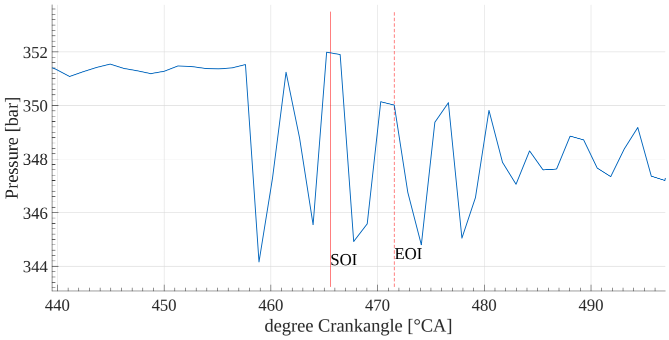

Fig. 4. Timing deviation between start of injection (SOI) and the corresponding sensor signal

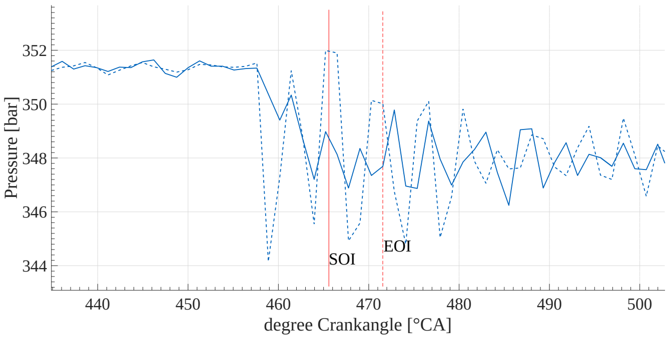

Fig. 5. Timing deviation between the actuator-near sensor and the fuel rail sensor signal

the two signals. For injectors further away from the rail pressure sensor, a slight delay is observed. However, in comparison to the deviation caused by the closed-loop controller for injection timing, it is negligible.
The following boundary conditions are extracted from signal analysis regarding model development:

- The pressure progression at the fuel rail pressure sensor will be modeled neglecting deadtimes and damping. No transfer function from the actuator to the location of the pressure sensor will be used. This will cause a small model error for injectors far away from the pressure sensor. In comparison to the error due to closed-loop controlling of the injection timings, this modeling error is negligible.
- For proper calculation of the output error of the model, the raw signal will be filtered using a FIR filter with a passband frequency corresponding to the 60th engine order. The amplitudes of the high frequency oscillations affect the output error of the model, but do not add information for diagnostics. Therefore they are neglected
- There is no need for models describing the pressure signal progression between the actuation of two components as the pressure remains at a stable plateau in this timespan. Only actuations of components and the resulting changes in fuel pressure will be modeled.

4.3 Fault Simulation with Hardware Manipulation

Figure 6 illustrates the waveform of the rail pressure sensor while simulating a leakage on injector 1. For this simulation standard injectors are installed on cylinders 2, 3, and 4 and an injector with a 59% higher stationary mass flow is installed on cylinder 1. Injection 1, which is

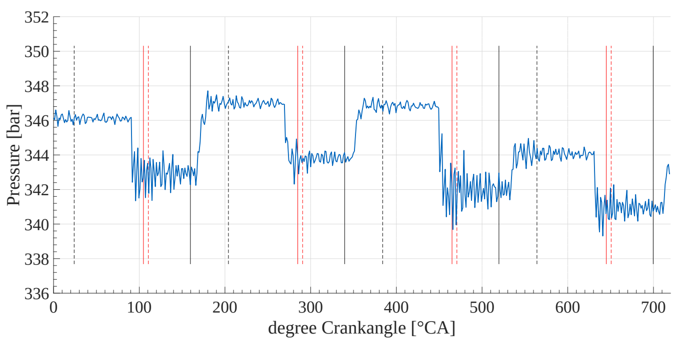

Fig. 6. Signal progression of the rail pressure sensor with a heavily leaking injector on cylinder 1.

actuated at 450°CA, induces a larger drop in pressure than the injections on the other cylinders. This shows that the ECU is not recognizing the difference in mass flow of the injectors and thus does not adapt injection duration on cylinder 1. Maintenance of a global stoichiometric mixture is realized through global lean out of all 4 cylinders.

5. DIAGNOSTIC MODEL

5.1 Model Architecture

Figure 7 shows a scheme of the architecture of the model. The measured data is cut into single CCs. In one of these

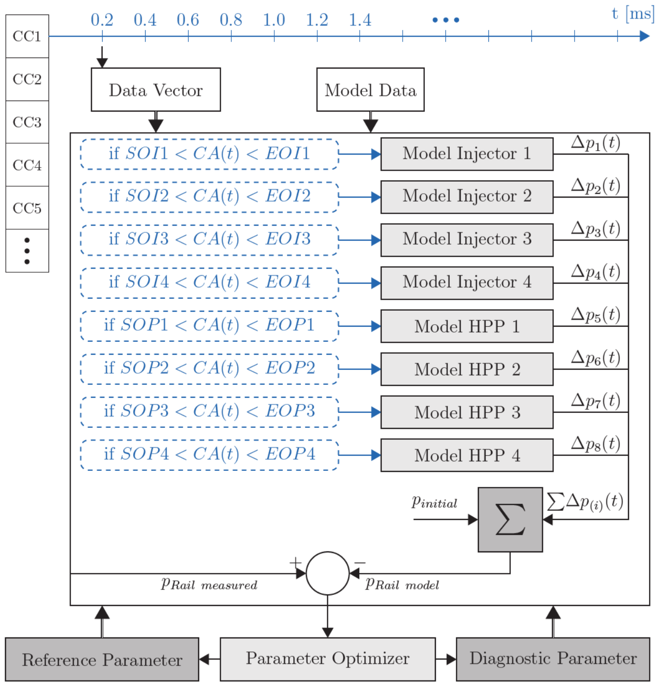

Fig. 7. Scheme of the parameter estimation model

CCs a state machine defines which actuator is active, so that the corresponding field of the *data vector* is used containing all the relevant measurement data:

- current engine speed and fuel rail pressure
- Crankangles of actuation of injectors, HPP and FCV

The *model data* block delivers time invariant information about the system, like the volume of the fuel rail, the sonic speed, and the coefficient of compressibility of gasoline Surek [2007], as well as the characteristic curves of the HPP and the injectors. For the investigated systems eight actuations are sequentially worked through, as each of actuators affect the system within a defined area of CA.
Each of the two parameter vectors (*reference parameters* and *diagnostic parameters*) contains 16 parameters for optimization: For each of the four injectors and pump strokes there is one parameter for timing offset and one for scaling the extent of Δp. Initially, all the scaling parameters of both vectors are set to a value of 1 and the timing offset parameters of both vectors are set to a value of 0.
The two sets of parameters are always used in combination but for different purposes: The *reference parameter* vector contains parameters, which are tuned for the reference state of the fuel system. As soon as the optimization of the *reference parameter* vector is completed, its values are frozen. When the diagnosis is executed on a vehicle showing ER, only the *diagnostic parameter* vector is used for parameter optimization. If the high pressure fuel system of the investigated engine does not show any faults, all the *diagnostic parameters* will remain at their initial values because the *reference parameter* vector does still describe the system's behavior correctly. If there is a fault present in the high pressure fuel system, the corresponding *diagnostic parameter* is adjusted by the parameter optimizer to obtain a simulated fuel pressure signal with a minimum deviation to the measured signal progression.
The single CCs are processed consecutively and a set

of *parameters* is optimized for each CC. After the optimization process is finished, a parameter vector is stored describing the system's behavior at a single CC. Doing so for multiple CCs and predefined or event triggered time intervals a matrix for statistical analysis is available, where each column contains the information of the one CC. This way stochastic deviations, aging of components, and faults can be seperated.
The sub-models in Figure 7 for the injectors (Model Injector (i)) and the HPP (Model HPP (i)) use the component's characteristic curves of volume flow and the compressibility equation to calculate a Δp in each time step if they are within their actuation time $CA(t)$. Δp resulting from the injector model are always negative, as they take fuel out of the system. Δp resulting from the HPP are always positive since fuel volume is added to the control volume.

5.2 Optimization Algorithm

The model of the high pressure fuel system is a blackbox for the optimizer. Multidimensional optimizer like the Nelder-Mead Downhill Simplex Algorithm Lagarias et al. [1998] Geiger [1999] tend to converge towards local minima instead of finding a global optimum, which causes a not acceptable rate of mis-optimizations.
Each of the 16 parameters affects a specific, unique section of the pressure signal progression within a CC. Therefore, a sequential, one dimensional optimization algorithm can be used for each parameter separately. The parameters are optimized consecutively according to the order of their area of impact. As described in Brent [1973] the optimizer is based on golden section search and parabolic interpolation inbetween predefined boundaries. Furthermore, by investigating the physical signal progression as described these boundary conditions can be set precisely and the algorithm does not consume much computing power, which is essential for on board diagnostics.

6. DIAGNOSTIC RESULT

The developed method was successfully evaluated for four different injector faults at two operating points of the engine. In the following, the test case of a sooted injector on cylinder 1 will be presented exemplarily.
The simulated and the measured signal progression of this

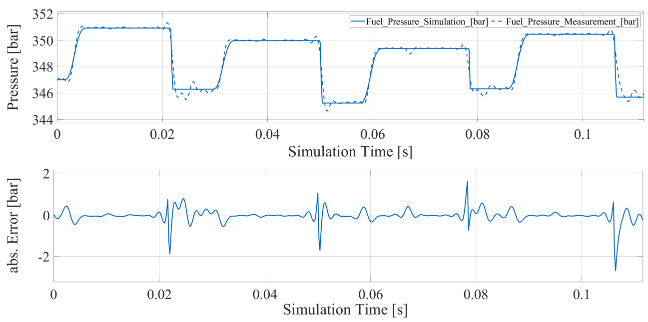

Fig. 8. Signal Progression of simulated and measured pressure in the fuel rail with calculation error

test case, and the progression of the simulation error are shown in Figure 8. The simulated signal is able to follow the measured signal almost exactly. The areas of constant plateaus are represented very accurate, which is essential for precisely diagnosing added or removed fuel mass. The relative calculation error averaged over the CC for this simulation results in 2.46%. Most of this error is caused by deviations resulting at the signal edges. The exact optimization of the edges has no influence on the scaling of the *diagnostic parameters*, which are used to detect the amount of deviation of injected fuel. The relative error is calculated referring to the difference between the highest and the lowest measured pressure value during the CC. The *reference parameters* for the injectors in this case accept the values shown in Figure 9.
In the case of an injector on cylinder 1 with a mass flow of

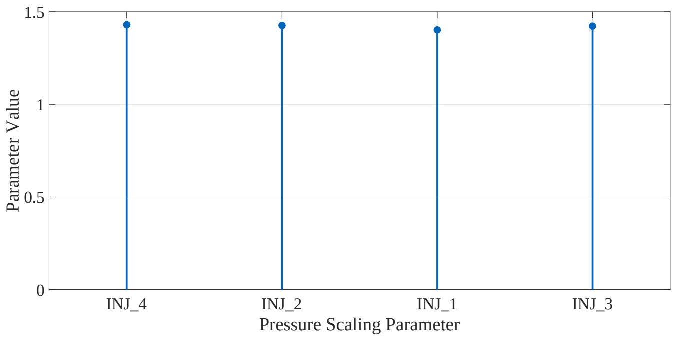

Fig. 9. *reference parameters* for scaling the pressure decreases of each injector (for reference state) presented in firing order.

37% lower compared to the injectors on cylinders 2, 3 and 4, the *diagnostic parameters* for the pressure drops, caused by each injector, accept the values depicted in Figure 10.
The *diagnostic parameter* for the pressure drop caused

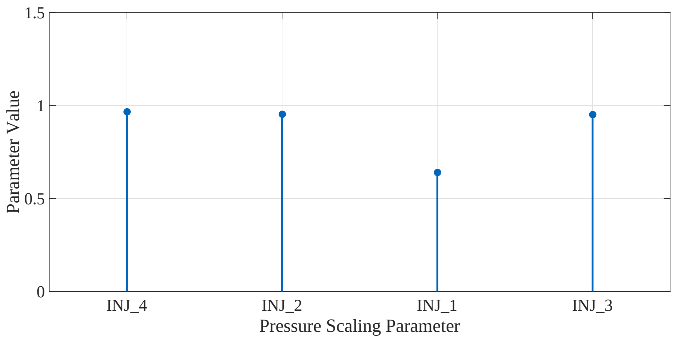

Fig. 10. Scaling of the *diagnostic parameters* for the simulation of sooted injector 1, presented in firing order.

by injector 1 is scaled to a value of 0.64 by the optimizer. The scalings of the *diagnostic parameters* of injectors 2, 3 and 4 remain at a value near 1 as there is no deviation to the corresponding reference state. The link between flow velocity c and pressure p in relation to density ρ is defined by Bernoulli's Equation Surek [2007].

$$\frac{c^2}{2} + \frac{p}{\rho} = const. \tag{2}$$

In equation 2, external energy input and changes in potential energy are neglected. According to this physical law, the pressure drop should correlate with the volume flow by the power of two. Instead, the diagnostic value correlates linearly with the change in mass flow through the injector. This is caused by the characteristic curve of the injector, which is used in the model. The *reference parameters* result from measurements of injectors with a stationary mass flow of 59% higher than the standard injectors, even though the injector's characteristic curve, which is stored in the model is valid for the standard injectors. The general shape of the curves is identical for all the injectors, but they deviate in deadtime behavior. Especially in operating points with low loads like in the investigated case this phenomenon has a high significance. In a production vehicle, there is a valid characteristic curve available for the installed injectors. Therefore, the correlation between mass flow deviation and the adapted values of the *diagnostic parameters* is expected to respect the physical laws more accurate.

Even though the parameter do not act as expected regarding Bernoulli's Equation, they deliver highly accurate information about the state of health of each injector. The location of the faulty injector, the type of fault, and its extent are detected correctly.

In order to reconfirm the results, a diagnosis on data from a reference state is conducted. This test aims to ensure that the parameters remain at a value near 1, if no fault is present in the high pressure fuel system. In Figure 11, the adapted parameters for steady state driving at a speed of 60km/h with no faults in the fuel system are shown.

Observing a healthy fuel system, the *diagnostic parameters* do not deviate more than 2.5% from the initial value.

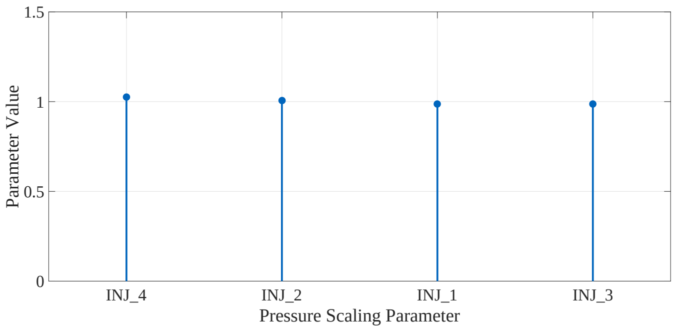

Fig. 11. Pressure scaling *diagnostic parameters* of the injectors for the reconfirmation test

The analyzed example demonstrates that the developed method is able to reproduce the fuel rail pressure signal accurately. From the values which are accepted by the optimized *diagnostic parameters*, detailed information about the state of health is extracted. If there is no fault present, the *diagnostic parameters* remain at a value near 1.

7. CONCLUSION

The outcome of the investigation is a diagnostic method, which is able to detect deviations in pressure progression caused by deviating mass flows of components of the fuel system in a reliable manner and an early state of degradation. Therefore, the potential for implementation in predictive diagnostic concepts concerning ER is considered high.

A possible implementation of the method in production vehicles is to learn the *reference parameters* after the initial engine start in the factory. As soon as the usage of the car starts, the degradation of the fuel system components is monitored and the *diagnostic parameters* deliver constant insights to the state of health of the fuel system. To do so the vehicle needs to store temporarily a short snapshot during the relevant operating point, to send the data over the air to a central computing unit where the method is executed. Further advanced statistical analysis during offline calculation of the *diagnostic parameter* matrix allows for detection of stochastic, intermittent, or incipient faults as well as for derivation of trends regarding aging and abnormal degradation. Thereby also faulty data can be examined by sending the boundary conditions during the measurement and comparing the results with a reference development fleet.

Since the entire high pressure fuel system of the engine was modeled, the method can be used for analyzing various faults of the HPP, the FCV, the fuel rail itself and other components.

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