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# Model Based Failure Detection of Diesel Particulate Filter

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*Abstract*— **Improvements in diesel engine technology have resulted in their expanded usage as powertrains in automotive applications. The Diesel Particulate Filter (DPF) is a common component of the exhaust after-treatment system of Diesel engines that removes the harmful Particulate Matter (PM) in the exhaust gas. To ensure that the filter is able to reduce PM levels of the diesel exhaust below regulated limits, On Board Diagnostics (OBD) of DPFs is required to provide alerts in the case of filter malfunction or failure. In the present study a method for performing the failure detection of Diesel Particulate Filter is proposed based on an adaptive model based technique. To detect a failure the coefficients of a healthy model of the pressure difference across the filter are compared with the adapted model coefficients since the presence of failure alters the dynamics of the system. This approach is robust to modeling errors, sensor noise and process variability and has OBD capability without the need of any additional sensors. The proposed approach is experimentally validated on a federal test procedure (FTP-75) drive cycle for healthy and failed filters in a heavy duty diesel engine test cell.**

## I. INTRODUCTION

High fuel economy, torque and efficiency have long ago made the diesel engines an obvious choice for heavy duty automotive applications. Recent advances in the field of diesel engine technology have improved the power, drive-ability and cost thereby increasing their popularity for light duty applications as well. This can be seen by the fact that the diesel engine market in Europe has reached almost 40 percent and is growing in US too [1]. One of the drawbacks of the diesel engines is the emissions of $NO_x$ and particulate matter. Due to the harmful effects of these emissions government agencies around the world have imposed increasingly stringent emission norms. Table I shows the PM regulation for heavy duty diesel engines in US [2] and the table II shows the corresponding PM emission norms in Europe . Emission limits in other countries are presented in.

TABLE I
PM EMISSION NORMS IN US

| Year | HDV PM(g/bhp-hr) |
|---|---|
| 2007 | .01 |
| 2010 | .01 |

The increasingly tighter emission limits of PM is usually enforced by the Diesel Particulate Filter which is a diesel engine exhaust gas treatment device that filters the PM or

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TABLE II
PM EMISSION NORMS IN EUROPE

| Emission Standard | Year | HDV PM(g/kWh) |
|---|---|---|
| Euro IV | 2005 | .10 |
| Euro V | 2008 | .02 |

soot. The above shown limits of PM should be met for the full useful life of the filter which in US is considered to be around 435000 miles [2]. The failure to do so would result in the soot emission from the filter exceeding the permissible limit. To prevent this, the OBD system mandated by the Environmental Protection Agency (EPA) and the California Air Resources Board (CARB) requires continuous monitoring of Diesel Particulate Filter. In case of a failure of the DPF the engine control module should be able to alert the vehicle driver.

OBD of the DPF device is the motivation of the present study. A Parametric Adaptive Model based failure detection method is proposed which can be used for OBD to detect the failure of a Diesel Particulate Filter that results in emission level of PM exceeding the legal limits. The proposed method uses a mathematical model of the pressure difference across the filter and the change in the coefficients of the model due to the presence of a failure is exploited for failure detection.

Conventional DPF failure detection is based on analyzing the pressure difference signals. The delta pressure measurement just after complete regeneration is compared with that of the known value of the pressure drop of healthy filter. This approach is shown to be highly sensitive to sensor noise and leads to very large threshold values for failure criteria [3]. Other methods of DPF failure detection are off-line and lack real time OBD capability or involve additional sensor costs [4],[5].

The model based approach presented in this paper does not involve any additional sensor costs and can be effectively used for OBD of DPF. The method uses orhthogonal least squares (OLS) estimation for model structure and parameter determination and is robust against modeling errors and sensor noise. The effect of process variability is taken into account by employing a threshold on the magnitude of the coefficient changes. The presented approach is validated using experimental results obtained from both healthy and failed DPFs.

## II. Diesel Particulate Filter Review

Presented in this section is the overview of the process of trapping PM by DPF and the phenomena of regeneration and the conditions under which a DPF fails. The model of pressure drop across DPF obtained from first principles is also shown. The DPF is used to trap the PM which is typically less than $10\mu m$ in size, present in the diesel engine exhaust [6]. The most common type of filter used in practice is ceramic extruded honeycomb wall flow filter. This type of filter consist of honeycomb substrate and is typically made from cordierite or silicon carbide.
The working principle of a DPF can be explained in terms of its two operating regimes, namely the loading regime and the regenerating regime. In the loading regime a filter captures the particulate matter in the exhaust gas and gets loaded. Fig. 1 shows the flow path of the exhaust gas in a filter. The substrate of the filter consists of a number of channels half of which are plugged at the inlet end and the rest half are plugged at the outlet end. The gas enters the unplugged inlet channel and is forced through the wall of the channel to exit from the adjacent open outlet channel. Hence, as the gases pass through the channel wall the particulate matter gets trapped.

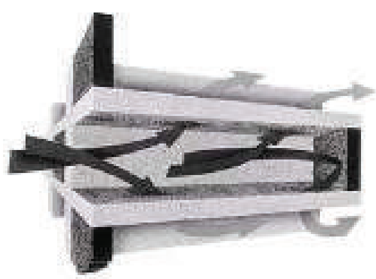

Fig. 1. Flow pattern in wall flow monolith

The filtration efficiencies of wall flow filters are very high (greater than 90 percent) which results in quick accumulation of particulate matter. This increases the resistance to flow of the exhaust gases which is an unfavorable condition since it results in increased fuel consumption. To overcome this problem the trapped PM is oxidized by burning and removing it from the filter, in a process called regeneration. A number of different methods can be used for filter regeneration as presented in [6],[7]. All these methods serve to increase either the temperature of the exhaust gases or make the filter environment more reactive to aid in the oxidation of PM.

### *Causes of DPF failure*

The major causes of DPF failure are thermal and mechanical stresses [6]. Thermal stresses are produced by high temperatures during the regeneration process. Very high temperature spikes can occur during soot oxidation under certain favorable conditions of high oxygen content in the filter which can cause cracking or melting of the filter. Mechanical stresses in the filter are produced by vehicle and engine vibrations. These stresses can lead to failure of filter wherein the filter will not be able to trap the particulate matter with full efficiency.

### *Delta Pressure Model from First Principles*

The pressure drop across the filter depends on the flow models characterizing the flow of exhaust gases in the inlet and outlet channels, across the soot layer and the filter wall and flow entrance and exit effects [8],[9]. An analytical expression of the filter pressure drop derived from first principles is shown in [8].The authors used a one dimensional model based on solution of mass and momentum conservation equations in a single channel of DPF and with zero initial soot loading, for pressure drop formulation. This model was later extended in [7] for arbitrary initial filter loading and verified by performing simulations and experiments. The expression derived in [7] is given below

$$\Delta P = \frac{\mu Q}{2V}(\alpha + w_s)^2 \left[ \frac{w_s}{k_0 \alpha} + \frac{1}{2K_{soot}} ln \left( \frac{\alpha}{\alpha - 2w} \right) + \frac{4Fl^2}{3} \left( \frac{1}{(\alpha - 2w)^4} + \frac{1}{\alpha^4} \right) \right] \tag{1}$$

where,
V= volume of filter
Q=exhaust gas flow through the filter
$\mu$ =exhaust dynamic viscosity
$\alpha$ =filter cell size
$w_s$ =filter wall thickness
$k_0$ =clean filter wall permeability
$K_{soot}$ =particulate layer permeability
$w$ =particulate layer thickness
$l$ =Effective channel length
$F$ =factor equal to 28.454

The above expression for delta pressure can be represented by a lumped parameter model written as

$$\Delta P = RQ \tag{2}$$

where R is the resistance to flow given by

$$R = \frac{\mu}{2V}(\alpha + w_s)^2 \left[ \frac{w_s}{k_0 \alpha} + \frac{1}{2K_{soot}} ln \left( \frac{\alpha}{\alpha - 2w} \right) + \frac{4Fl^2}{3} \left( \frac{1}{(\alpha - 2w)^4} + \frac{1}{\alpha^4} \right) \right] \tag{3}$$

The above expressions show that delta pressure depends on flow of the exhaust gases and the resistance to flow offered by the filter. The resistance in turn depends on the microstructural and geometrical properties of the filter and temperature of the flowing gases (soot permeability and exhaust gases viscosity are temperature dependant [7]) in the DPF.

## III. Proposed Failure Detection Method

In this section the proposed online method to detect a failed DPF is presented. The present study utilizes an adaptive model based failure detection method such that the model output tracks the sensor measurement. This model based approach is based on the dynamics of the system which is affected in the presence of a failure. The changes in the coefficients of the adapted model from that of the healthy model forms the basis of the failure detection. The mathematical model of pressure differential across the DPF will be used for this purpose where the model structure as well as the coefficients of the model are identified using orthogonal least squares based algorithms which reduces the modeling errors and the effect of sensor noise. Moreover the change of coefficients are used for failure detection rather than their absolute values which further reduces the effect of modeling errors. The effect of process variability is taken into account by employing a threshold for the magnitude of changes of the coefficients based on the standard deviation of the computed healthy coefficients.

*1) Orthogonal Least Squares:* Orhthogonal least Squares algorithm can be efficiently used for black box modeling of the unknown system. It identifies the regressors of the model from a large number of possible permutations obtained by input and output combinations. OLS introduces an auxiliary model defined such that the terms in the model are orthogonal over the data set and evaluates the effect of each regressor in reducing the output variance which is also known as error reduction ratio (ERR) [10],[11]. The algorithm uses this criterion to select the model regressors until a point of diminishing return is reached. Additionally OLS also estimates the parameters of a linear and linear in parameters non-linear model with respect to each input sequentially and independently of other inputs. Under the conditions of persistent excitation, consistent estimates can be obtained even in the presence of correlated noise.
The inputs required by the OLS are different regressors, the maximum number of terms desired in the model and the maximum power that the regressor combinations can be raised to. To reduce the modeling errors, this information in the present case will be obtained from a physics based model of the delta pressure of DPF. This process correlates the physics based model with the OLS obtained black box model.

The above procedure of model structure and parameter estimation using OLS and the physics based model results in robustness against the modeling errors and the sensor noise.

*2) Threshold Evaluation:* In the present study the presence of a failure in the system is detected by evaluating the coefficient error vector against a threshold that represents system variability. The coefficient error vector is obtained by comparing the healthy model coefficients with adapted model coefficients that may or may not contain a failure. In the presence of failure the coefficient error vector points to specific fault in the fault space. A generalized representation of fault space is shown in fig. 2 which shows three distinct fault spaces which could correspond to three different possible faults of the system.The origin of the fault space represents the healthy system and the radius of each fault space is a result of system variability possibly due to, among other things, sensor noise and accuracy.
Let the healthy model coefficients be represented by

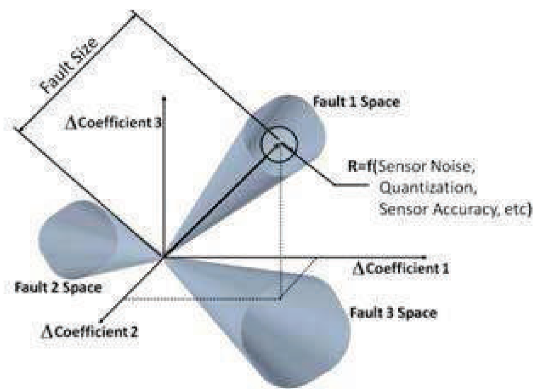


Fig. 2. Fault Space

$$H = [h_1, \dots, h_n] \in R^n$$

where n is the number of model coefficients and let the adapted model coefficients obtained by online parameter estimation be represented by

$$F = [f_1, \dots, f_n] \in R^n$$

The coefficient error vector or the residual is then obtained by the following equation

$$E = D(H^T - F^T)^T \tag{4}$$

where,

$$D = diag\left[\frac{1}{h_1}, \dots, \frac{1}{h_n}\right] \tag{5}$$

The matrix D is used to normalize each coefficient. Detecting the presence of a failure can be accomplished by evaluating the magnitude of E and ensuring that this error is not due to the standard variability of the system. Hence a failure would be detected if

$$\| E \|_2 > \epsilon \tag{6}$$

where,
$\| E \|_2 = \sqrt{\sum_{i=1}^{n} | E(i,1) |^2}$

Here $\epsilon$ is the threshold value that represents the degree of variability of the system. This threshold can be calculated by statistical analysis of the coefficients of the model.
In the present study the coefficients are identified by performing a number of experiments. The mean of the values

obtained from different experiments represents the true value of the coefficients and the standard deviation of each of the coefficient is used to determine $\epsilon$.

$$\epsilon = \| 3\sigma_{h_1}, \ldots, 3\sigma_{h_n} \|_2 \tag{7}$$

The value of $3\sigma_{h_i}$ corresponds to 99.73 % confidence interval assuming a normal distribution of obtained values of coefficients from different experiments.

## IV. Experimental Validation of failure Detection Method

The data used in this study was obtained from tests performed on a Cummins heavy duty diesel engine equipped with a cooled exhaust gas recirculation (EGR) system and a variable geometry turbocharger system (VGT) in a test bench with a dynamometer capable of running transient speed load maps. Federal test Procedure (FTP-75) cycle was used to collect data for wide operating points of DPF operation. Closed loop EGR and VGT valve control was in effect during these cylces to test the DPF for real world situations.

*Types of Filters*
For failure detection data was provided by Cummins on two sets of filters. Each set had three filters with one production base filter which will be denoted as healthy filter and two failed filters . In the rest of the paper these would be referred to as dataset-1 and dataset-2.
Dataset-1 had artificially failed filters of different degree of severity. The filters were artificially failed by cutting away the outlet face of the DPF to remove the plugs, with various thickness (in the present case it is 2" and 3") and for a complete arc of the circle. This type of failure is known as Annular Milling and represents a type of real world failure of DPF. Dataset-2 had two real world field failed DPF's of unknown failure. Table III shows the different filters present in each of the dataset. The dimension of filters in both the data set are different and is shown in Table IV.

TABLE III
FILTER DESCRIPTION OF EACH DATASET

| Data Set 1 | Data Set 2 |
|---|---|
| Healthy Filter | Healthy Filter |
| 2" Annular milling | Failed Filter-1 |
| 3" Annular Milling | Failed Filter-2 |

TABLE IV
FILTER DIMENSION

| | Data Set 1 | Data Set 2 |
|---|---|---|
| Length | 12" | 12" |
| Diameter | 10" | 12" |

### A. *Main Results*

*1) Model Structure Identification:* As explained in section III the model structure for the pressure difference across the DPF would be identified using OLS, the input data for which will be obtained from the physics based model. The OLS algorithm is implemented on an entire FTP-75 cycle consisting of 1050 data points. This efficiently reduces the effect of sensor noise as large data length is used to estimate the parameters.

**Delta Pressure Model from Orthogonal Least Squares**
To identify the model regressors using OLS, flow through DPF, Q($m^3/s$) and diesel oxidation catalyst (DOC) outlet temperature, $T_{DOC}$ (degree K) were used and up to two backsamples of each of these variables were considered. DOC temperature is used instead of DPF temperature because DPF temperature sensor measures the filter outlet temperature. A maximum power of up to 3 that the regressors can be raised to and a total of up to 8 eight terms model where considered.
The model that gave minimum least squared error for all the filters was selected. The model as given by OLS is

$$\Delta P(t) = \phi^T(t)\theta \tag{8}$$

where,

$$\phi = [Q(t), T_{DOC}(t-1), Q(t) * T_{DOC}(t-1)]^T \tag{9}$$

and

$$\theta = [a_1, a_2, a_3]^T \tag{10}$$

The argument (t-1) denotes the first backsample of the variable since the sampling frequency of the experimental data is 1 rad/s.
This model was chosen since increasing the number of terms or the power of the regressors did not produce any significant improvement in the model output.

**Correlation of OLS and Physics Based Model**
The model obtained through OLS is

$$\begin{aligned} \Delta P &= a_1 Q(t) + a_2 T_{DOC}(t-1) + a_3 Q(t) T_{DOC}(t-1) \\ &= a_2 T_{DOC}(t-1) + (a_1 + a_3 T_{DOC}(t-1))Q(t) \\ &= a_2 T_{DOC}(t-1) + RQ(t) \end{aligned} \tag{11}$$

where,

$$R = a_1 + a_3 T_{DOC}(t-1) \tag{12}$$

It can be seen from (11) that the OLS based delta pressure model is in agreement with the physics based model (1) and also includes a bias term. The resistance in (12) as predicted from the physics based model depends on the temperature of exhaust gases entering the DPF. The presence of a backsample of DOC temperature in the model can be explained by the fact that DOC is placed before DPF and the temperature of gases entering the DPF at the current instant would correspond to temperature of gases leaving

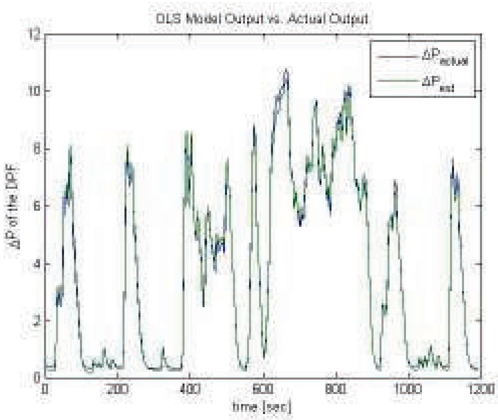


Fig. 3. Plot of Actual Output vs OLS Model Output for Healthy Filter Dataset-1

the DOC at one previous instant. This shows that the model obtained from OLS correlates well with the physics based model.
The tracking ability of the OLS generated model with that of the actual output is shown in Fig. 3 for the healthy system of dataset-1.

*2) Failure Detection of DPF- Dataset-1:* Data Set-1 had one healthy filter and two artificially failed filter through annular milling of size 2" and 3" respectively. For each filter four FTP-75 test cycle runs were performed and sets of four values of each coefficient of the model and for all the filters were found. The mean value in each set was considered to be the true value and standard deviation was calculated of the coefficients of the healthy system. Table V shows the mean estimated coefficients of the filters in dataset-1. The coefficients have been normalized to address the significant difference in the magnitude of the coefficients.

TABLE V
OLS ESTIMATED COEFFICIENTS DATASET-1

| Type of Filter | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|
| Healthy Filter | 1.2944 | -1.2861 | 9.8996 |
| 2" Annular milling | 0.3141 | -0.6175 | 7.276 |
| 3" Annular Milling | 0.2729 | -0.1915 | 6.3742 |

The threshold for Data Set-1 is given by

$$\epsilon = \|\ 3\sigma_{a1}, 3\sigma_{a2}, 3\sigma_{a3}\ \|_2$$

For healthy filter $\epsilon = 0.1836$ . Now the error vector was defined in (4).
For 2" Annular Milling filter

$$E = [0.7573, 0.5199, 0.2650]^T$$

and $\|\ E\ \|_2 = 0.9286$

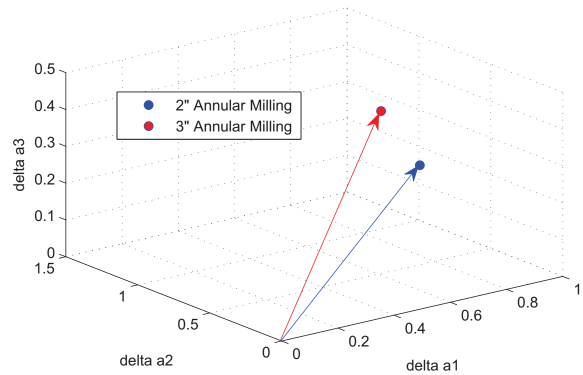


Fig. 4. Error Vectors in Fault Space Data Set-1

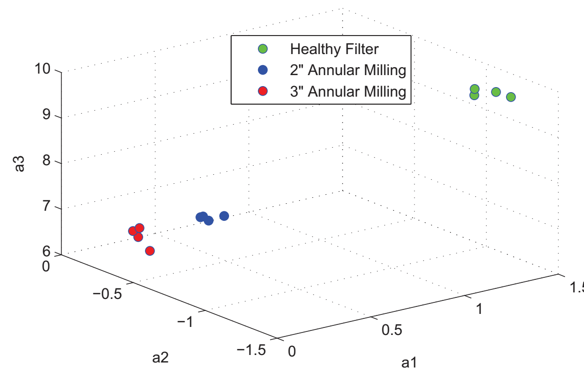


Fig. 5. Plot of Coefficients of the delta Pressure model for filters of Data Set-1

Since $\|\ E\ \|_2 > \epsilon$ hence a failure is present. Now for 3" Annular Milling

$$E = [0.7891, 0.8511, 0.3561]^T$$

and $\|\ E\ \|_2 = 1.1799$ again since $\|\ E\ \|_2 > \epsilon$ a failure is present.
Fig. 4 shows the error vector plots of the failed filters in the fault space. Failure estimation can be performed by analyzing the magnitude of the error vector as can be seen in Data Set-1. The magnitude of error vector corresponding to 3" Annular Milling is larger than that of the 2" Annular Milling vecor. Fig. 5 shows the 3-D plot of the coefficients of all the filters of Data Set-1.

*3) Failure Detection of real world DPF- Dataset-2:* This data set consists of one healthy filter and two real world failed filters with unknown failure modes. The OLS estimated, normalized mean values of the coefficients are shown in table VI. The coefficients of healthy filter of both the data-sets differ due to different filter geometry. This implies that in order to implement the proposed methodology baselining of the healthy filter is required.

TABLE VI

OLS ESTIMATED COEFFICIENTS DATASET-2

| Type of Filter | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|
| Healthy Filter | 1.1642 | 0.-7171 | 4.4778 |
| Failed Filter-1 | 0.4011 | -1.3019 | 11.0364 |
| Failed Filter-2 | 0.2766 | -0.7253 | 8.6513 |

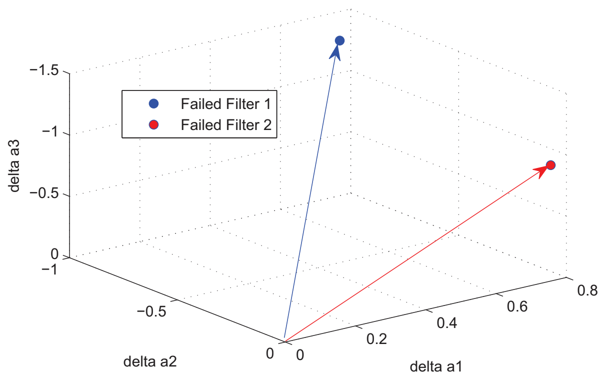


Fig. 6. Error Vectors in Fault Space Dataset-2

The threshold for this data set calculated from the healthy filter coefficients is given by $\epsilon = 0.3365$.

For Failed Filter-1 the error vector of coefficients is

$$E = [0.6554, -0.8154, -1.4646]^T$$

and $\|E\|_2 = 2.1725$

Since $\|E\|_2 > \epsilon$ hence a failure is present.

Now for Failed Filter-2

$$E = [0.7623, -0.0114, -0.932]^T$$

and $\|E\|_2 = 1.5227$ again since $\|E\|_2 > \epsilon$ a failure is present.

Fig 6 shows the plot of error vector of Data Set-2 in the fault space and Fig 7 shows the coefficient plot of all the filters.

## V. SUMMARY

An adaptive model based technique to detect the presence of failure in the Diesel Particulate Filter system is presented. This methodology can be used on board to alert the vehicle operator in case of failure of filter resulting in PM emission exceeding the legal limits. The mathematical model of the pressure difference across the filter is used for failure detection. The fact that in the presence of failure the dynamics of the system gets affected and the coefficients of the model would change to accommodate this effect is the concept behind the proposed failure detection methodology. The method is successfully implemented and validated to detect the failed filters from healthy ones through the engine test cell data on two sets of filters where each set had both healthy and failed filters.

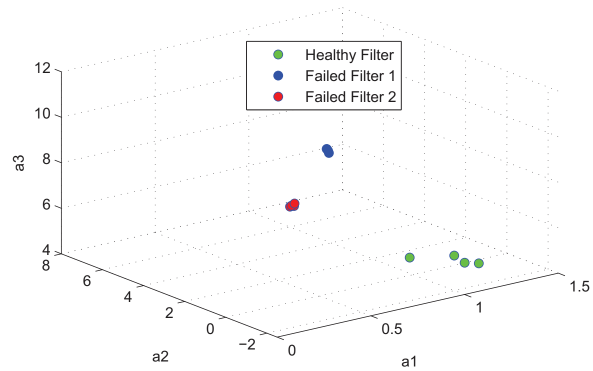


Fig. 7. Plot of Coefficients of the Delta Pressure Model for Filters of Dataset-2

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