In-cylinder Pressure Pegging Algorithm Based on Cyclic Polytropic Coefficient Learning

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ABSTRACT: This paper presents an in-cylinder pressure pegging algorithm based on cyclic polytropic coefficient learning for combustion engines. In order to take the cycle-to-cycle variation of the polytropic coefficient into account in the in-cylinder measurement, an iterative learning algorithm is proposed to provide cyclic estimation of the polytropic coefficient and then with the estimation cyclic compensation method is proposed for the offset of in-cylinder pressure measurement. A comparative study of the proposed algorithm, the least-squares method (LSM) with a fixed polytropic coefficient and the nonlinear least-squares method (NLSM) with a variable polytropic coefficient is conducted using the simulated pressure data. Experimental validations are conducted on a six-cylinder gasoline engine at a motored condition and a steady fired operation condition.

KEY WORDS: electronics and control, engine control, measurement/diagnosis/evaluation, pressure pegging [E1]

1. Introduction

In recent years, in-cylinder pressure based engine control is of great interest in order to improve fuel efficiency and reduce emissions. With ongoing pressure sensor cost reduction, engine equipped with pressure sensor is becoming the future trend of development. Among various sensors, piezo-electric transducers are usually used to measure the original in-cylinder pressure, due to their high transient response capacity (1). The piezoelectric transducer responds to pressure difference by outputting a charge referenced to an arbitrary ground, and the charge is transformed into voltage by a charge amplifier (2). Hence, the measured original pressure trace is relative and biased. Moreover, the sensor bias is affected by the high temperature variability which leads to the thermal drift (2). The measured original pressure must be precisely referenced to the actual absolute pressure, i.e., pegging, due to the significant influence of pegging error on combustion parameters calculation (3).

Regarding in-cylinder pressure pegging, many algorithms have been proposed (1-6). One normally used pegging algorithm is the linear least-squares method (LSM) with a known polytropic coefficient (5). This algorithm assumes that compression is a polytropic process with a fixed. If more than two measured samples are available in the compression process, the linear LSM will be applied to determine the sensor offset. This algorithm is simple and has the advantage of reduced computational burden. However, the polytropic coefficient has cyclic variations due to different engine operation conditions such as air-to-fuel ratio, engine load, air and cooling water temperature disturbances.

Hence, LSM is significantly affected by the uncertainty of the polytropic coefficient, i.e., the inaccurate polytropic coefficient value would lead to erroneous results (7). Moreover, the polytropic coefficient is also an important parameter which need to be estimated in some applications such as the trapped mass estimation based on $\Delta p$ method (8). To eliminate the adverse effects of fixed polytropic coefficient, a nonlinear LSM that calculate polytropic coefficient and offset by successive iterations, is recommended (4,6). By this algorithm, the polytropic coefficient and sensor offset will be evaluated simultaneously. But the computational cost of nonlinear LSM is high, i.e., many iterations might be required for sensor offset and polytropic coefficient evaluation during one cycle.

In order to alleviate the limitations of the mentioned two algorithms, a pressure pegging algorithm based on cyclic polytropic coefficient learning is proposed in this research. Assume that the polytropic coefficient is a constant during one cycle (intra-cycle) and slowly varying parameter for cycle-to-cycle (inter-cycle). Then the algorithm in this paper can be developed in two aspects. Firstly, let the polytropic coefficient in the current engine cycle equals to the value in the previous cycle, due to the slowly cyclic variation of polytropic coefficient. Applying the least-squares method can calculate sensor offset of the current engine cycle. Secondly, employ a cyclic modification on the polytropic coefficient value of previous engine cycle and the value of current engine cycle is obtained. The proposed method possesses advantages of both LSM and NLSM i.e., low computational cost and cyclic variation of polytropic coefficient.
A comparative study of the proposed method, LSM and NLSM is conducted using both simulated pressure data and experimental pressure data collected on a six-cylinder gasoline engine.

2. In-cylinder Pressure Pegging Methods

As stated before, the measured pressure must be referenced to absolute pressure, i.e., the sensor offset must be calculated, as shown in Fig.1. Let \( p^{\text{mea}} \) denote the measured original in-cylinder pressure from sensor with respect to crank angle during a combustion engine cycle which can be written as,

\[
p^{\text{mea}} = p - p^{\text{set}} + e
\]

(1)

where \( p \), \( p^{\text{set}} \), and \( e \) are the actual pressure, sensor offset, and random sensor noise which obeys a Gaussian distribution \(^{(2)}\), respectively. During compression process it can be assumed that there is no mass and heat exchange. Then with the hypothesis of polytropic compression, the following equation holds during the compression process,

\[
p_i V_i^* = p_i V_i^* = C
\]

(2)

where \( V_i \), \( V_i^* \), and \( p_i \), \( p_i^* \), are the cylinder volumes and actual pressures corresponding to two crank angles, \( C \) is a constant in a compression process, and \( \kappa \) is the polytropic coefficient which is usually suggested to be 1.32 for gasoline engines.

Fig.1 Measured pressure and absolute pressure after pegging

The most used pegging methods can be classified into three classes \(^{(1,3)}\). The first class methods utilize a pressure sensor in the inlet or exhaust manifold and let in-cylinder pressure value at a properly pre-defined crank angle equal to the measured pressure in inlet or exhaust manifold. This class of methods is sensitive to the measured noise of inlet or exhaust sensor and is limited to low engine speed. The second class methods assume that compression process is polytropic with a fixed polytropic coefficient \( \kappa_0 \). If two measured pressure samples are available during the compression process, the sensor offset can be calculated by equation (3). Otherwise, if more than two are available, the least-squares method (LSM) will be applied to determine \( p^{\text{set}} \). The third class methods assume that compression process is polytropic with a variable polytropic coefficient. If three different measured points are available, the variable polytropic coefficient \( \kappa \) can be approximated by Taylor series expansion at \( \kappa_0 \) \(^{(1)}\), thus the sensor offset can be calculated by equation (3) in which \( \kappa_0 \) is replaced by \( \kappa \). If more than three measured points are available, \( \kappa \) and \( p^{\text{set}} \) are determined by applying the nonlinear least-squares method (NLSM).

\[
p^{\text{set}} = p^{\text{mea}} - p^{\text{mea}} \cdot (V_i / V_i^*) \cdot (1 - (V_i / V_i^*))
\]

(3)

Among the above various pegging methods, LSM and NLSM can be mostly used to improve pegging accuracy and robustness to sensor noise.

2.1. Least-squares method (LSM) with a fixed polytropic coefficient

In this method, polytropic coefficient is considered as a known constant, \( \kappa_0 \). More than two measured pressure samples (sample size \( I > 2 \) ) during the compression process of a combustion cycle are utilized in LSM to determine the sensor offset,

\[
\text{arg min}_{C} \left( J(p^{\text{set}}, C) = \sum_{i=1}^{I} \left[ \{ p^{\text{mea}} + p^{\text{set}} - C \} V_i^{\text{set}} \} \right] \right)
\]

(4)

where the subscript \( i \) denotes the sample pressure index, \( (p^{\text{set}}, C) \) is the evaluated minimum with the known \( \kappa_0 \). \( p^{\text{set}} \) is the obtained sensor offset. Write equation (1) in a matrix form,

\[
p^{\text{mea}} = M(\kappa_0) \cdot x + e
\]

(5)

\[
p^{\text{mea}} = \left[ p_{1}^{\text{mea}}, p_{2}^{\text{mea}}, \ldots, p_{I}^{\text{mea}} \right]^T
\]

(6)

\[
M(\kappa_0) = \left[ \begin{array}{ccc}
-1 & -1 & \ldots & -1 \\
1 / V_1^{\text{mea}} & 1 / V_2^{\text{mea}} & \ldots & 1 / V_I^{\text{mea}}
\end{array} \right]^{T}
\]

(7)

\[
x^{*1} = \left[ \begin{array}{c}
p^{\text{set}} \\
C
\end{array} \right]
\]

(8)

\[
e^{*1} = [e_1, e_2, \ldots, e_I]^T
\]

(9)

Then equation (4) can be written in the following matrix form,

\[
x^* = \arg \min_x \left[ J(x) = \left\| p^{\text{mea}} - M(\kappa_0) \cdot x \right\|_E^2 \right]
\]

(10)

The parameter can be obtained by applying the LSM,

\[
x^* = (M(\kappa_0)^T \cdot M(\kappa_0))^{-1} \cdot M(\kappa_0)^T \cdot p^{\text{mea}}
\]

(11)

This LSM is simple and has the advantage of acceptable computational burden. However, the polytropic coefficient is variable cycle-to-cycle due to different engine operation conditions and stochasticity of engine cycle, such as the variations of variable valve timing, load, air-to-fuel ratio, air and cooling water temperature. The estimation of sensor offset is significantly affected by the uncertainty of the polytropic coefficient, i.e., the inaccurate \( \kappa_0 \) would lead to erroneous results. To eliminate the adverse effects of fixed \( \kappa_0 \), a nonlinear LSM that calculate polytropic coefficient and sensor offset simultaneously is recommended.
2.2. Nonlinear least-squares method (NLSM) with a variable polytropic coefficient

Consider the cyclic variation of polytropic coefficient, \((\kappa^*, p^*, C^*)\) can be estimated simultaneously by applying the NLSM.

\[
(\kappa^*, x^*) = \arg \min_{\kappa, x} J(\kappa; x) = [p^* - M(\kappa) \cdot x^*]^2
\]  

\[(12)\]

It’s difficult to obtain an analytical solution for the above nonlinear least-squares problem. Iterative method is usually employed to get a numerical solution. The iteration algorithm can be described in following steps:

**Initialization**: \(\kappa_0\)

**FOR** \(r = 1: N\)

**Step 1**: given \(\kappa_{n-1}\), apply LSM to obtain \(x(\kappa_{n-1})\),

\[
x(\kappa_{n-1}) = (M(\kappa_{n-1})^T \cdot M(\kappa_{n-1}))^{-1} \cdot M(\kappa_{n-1})^T \cdot p^*
\]  

\[(13)\]

**Step 2**: Estimate the gradient and second derivative,

\[
g(\kappa_{n-1}) = \frac{dJ}{d\kappa} \left(\kappa_{n-1}, x(\kappa_{n-1})\right)
\]

\[
G(\kappa_{n-1}) = \frac{d^2J}{d\kappa^2} \left(\kappa_{n-1}, x(\kappa_{n-1})\right)
\]

**Step 3**: Update \(\kappa\) at the \(k^{th}\) iteration by Newton’s method,

\[
\kappa_k = \kappa_{n-1} - G^{-1}(\kappa_{n-1}) \cdot g(\kappa_{n-1})
\]

\[(16)\]

It should be noted that \(\kappa\) denotes the iteration order during one engine cycle. This NLSM takes the cyclic uncertainty of polytropic coefficient into account, hence the disadvantage of LSM caused by the fixed \(\kappa\), which may be inaccurate can be eliminated. However, the computational cost of nonlinear LSM is high, i.e., many iterations might be required for offset and \(\kappa\) evaluation during one cycle.

3. Least-squares Method with Polytropic Coefficient Cyclic Learning

Both of the LSM with fixed polytropic coefficient and the NLSM with variable polytropic coefficient have limitations of either inaccuracy from fixed \(\kappa_0\) or high computational cost. In order to alleviate the limitations of the mentioned two methods and balance the calculation precision and the computational cost, a pressure pegging algorithm based on least-squares method with polytropic coefficient cyclic learning (abbreviated to \(\kappa\)CL-LSM) is proposed in this research.

Assume that the polytropic coefficient is a constant during one cycle (intra-cycle) and a slowly varying parameter for cycle-to-cycle (inter-cycle). Based on the assumptions, the idea of \(\kappa\)CL-LSM is developed in two aspects. Firstly, let the polytropic coefficient in the current engine cycle equals to the value in the previous cycle, due to the slowly varying cycle of polytropic coefficient. Applying the least-squares method can calculate sensor offset of the current engine cycle,

\[
x_n(\kappa^{*}_{n-1}) = \arg \min_{\kappa_n} J_n(\kappa_n) = [p^{*}_n - M(\kappa^{*}_{n-1}) \cdot x^{*}_{n}]^2
\]

\[(17)\]

\[
x_n(\kappa^{*}_{n-1}) = [p^{*}_n(\kappa^{*}_{n-1}) \cdot C_n^{*}(\kappa^{*}_{n-1})]^T
\]

\[(18)\]

where the subscript \(n\) denotes the current engine cycle sequence number, \(\kappa_{n-1}\) is the polytropic coefficient of previous cycle. Secondly, employ a cyclic modification on the previous \(\kappa_{n-1}\) and the current \(\kappa_{n}\) is obtained.

Then the proposed \(\kappa\)CL-LSM can be described in following steps:

**Initialization**: \(\kappa_0\)

**FOR** \(n = 1: N\)

**Step 1**: **Intra-cycle**: given \(\kappa_{n-1}\), apply the LSM to obtain \(x(\kappa_{n-1})\),

\[
x_n(\kappa^{*}_{n-1}) = (M(\kappa^{*}_{n-1})^T \cdot M(\kappa^{*}_{n-1}))^{-1} \cdot M(\kappa^{*}_{n-1})^T \cdot p^{*}_n
\]

\[(19)\]

**Step 2**: Estimate the gradient,

\[
g_n(\kappa_{n-1}) = \frac{dJ}{d\kappa} \left(\kappa_{n-1}, x_n(\kappa_{n-1})\right)
\]

\[-2\kappa_{n-1} \cdot [V(\kappa_{n-1} + 1), C_n^{*}(\kappa^{*}_{n-1}) \cdot [p^{*}_n - M(\kappa^{*}_{n-1}) \cdot x^{*}_{n}]^T
\]

\[(20)\]

**Step 3**: **Inter-cycle**: Cyclic learning of \(\kappa\) at the \(n^{th}\) engine cycle by gradient descent method,

\[
\kappa_n = \kappa_{n-1} - \Gamma \cdot g_n(\kappa_{n-1})
\]

\[(21)\]

It should be noted that the form (21) is the cyclic iteration in contiguous engine cycles (inter-cycle), while the form (16) is the iteration during one engine cycle (intra-cycle). The proposed \(\kappa\)CL-LSM possesses advantages of both LSM with a fixed polytropic coefficient and NLSM with a variable polytropic coefficient, i.e., low computational cost and cyclic variation of polytropic coefficient.

A comparative study of the proposed \(\kappa\)CL-LSM, the LSM and the NLSM is conducted using both simulated pressure data and experimental pressure data collected on a six-cylinder gasoline engine.

4. Simulation Results

4.1. Simulated pressure data

Assume the polytropic coefficient and sensor offset of each engine cycle are exactly known as shown in Fig.2. The polytropic coefficient trace of 2000 adjacent engine cycles is simulated as a sine wave with a period of 300 engine cycles which imply \(\kappa\) is a slowly varying parameter. The sensor offset \(p^*_n\) and \(C_n\) are set as constants 0 (bar) and 0.34, respectively. Based on the knowledge shown in Fig.2, the measured pressure during compression process can be simulated by,
\[ p_{mea}^{\kappa} = \frac{C_n}{V^{\kappa}} - p_{e}^{\kappa} + \varepsilon_n \]  \tag{22}

where \( \kappa, p_{e}^{\kappa}, C_n \) are the pre-set simulated parameters shown in Fig.2, \( V \) is the cylinder volume which is also known, \( \varepsilon_n \) is the random sensor noise which is assumed to be white Gaussian noise, as shown in Fig.3 which is collected from a gasoline engine targeted in this research by Kistler 6052CU20. The sensor noise at some sample points are obviously abnormal, i.e., the noise amplitude is very large as shown in Fig.3. We do not consider such abnormal value and just take account of the noise bounded in an acceptable boundary when do statistical analysis of the sensor noise. The expected value and standard deviation of sensor noise in each engine cycle is shown in Fig.4. It’s obvious that the expected value is around zero and the standard deviation is around 0.03. Hence, it can be assumed that the sensor noise obeys,

\[ \varepsilon_n \sim N(0,0.03^2) \]  \tag{23}

The range of crank angle for the pressure samples should be after intake variable value timing (IVVT) close and before ignition. In this study, the IVVT closes at 109° BTDC (before top dead center) and spark advance is 23° BTDC. Hence, we set the range as 100° BTDC ~ 40° BTDC crank angle degree (CAD).

Then the simulated measured pressure can be obtained by equation (22), as shown in Fig.5. Moreover, Tunestål Per concluded that the standard deviation of the estimate roughly drops as \( 1/\sqrt{I} \) with the sample size \( I \) \(^{(5)}\). Larger sample size results in more precise estimate, however, the computational cost will be increased. Assume the pressure is sampled every one CAD, then there are 61 pressure sample points during 100° BTDC ~ 40° BTDC in one combustion are available. Utilize the simulated measured pressure of 2000 engine cycles, the estimated sensor offset and polytropic coefficient by LSM, NLSM and CL-LSM can be compared directly.

4.2. Comparison of three pressure pegging methods

Firstly, the least-squares method (LSM) with a fixed polytropic coefficient value which is assumed to be 1.32 (the mean value of simulated polytropic coefficient sine wave shown in Fig.2) is applied for the simulated pressure data of 2000 engine cycles.

Secondly, the nonlinear least-squares method (NLSM) with an unknown variable polytropic coefficient is employed for the same group of simulated pressure data. The iterative algorithm described in Section 2.2 is applied to get numerical solutions. During one engine cycle, a lot of iterations might be required to
estimate the polytropic coefficient $\kappa$ and the sensor offset $p^\omega$ simultaneously. Fig. 6 shows the iterative process of three adjacent engine cycles. With enough iterations in each engine cycle, all of the polytropic coefficient $\kappa_i$, sensor offset $p^\omega_i$ and residual error $J_i$ of least-squares fitting converge to their stable values.

![Image of iterative process](image)

**Fig.6 Nonlinear least-squares method iterative process**

Thirdly, the proposed $\kappa$ cyclic learning least-squares method (CL-LSM) with an unknown variable polytropic coefficient is employed for the same group of simulated pressure data. The cyclic iterative algorithm $\kappa$CL-LSM described in Section 3 is applied to estimate cyclic polytropic coefficient. Fig.7 claims that the step size $\Gamma$ is a significant parameter affects the performances of sensor offset and polytropic coefficient estimation. The mean value and standard deviation of parameter estimation error are plotted in Fig.7 from which the best step size is selected as $10^{-3.4}$ ($\lg(\Gamma) = -3.4$).

The comparisons of the mentioned three methods are illustrated in Fig.8, Fig.9 and Fig.10. As shown in Fig.8, both of the polytropic coefficient traces estimated by NLSM and $\kappa$CL-LSM can track the actual simulated sine wave. The value from NLSM has severe oscillation, while the value from $\kappa$CL-LSM is more stable and more closed to the actual simulated sine wave. The sensor offsets evaluated by NLSM and $\kappa$CL-LSM also have similar characteristics, i.e., $\kappa$CL-LSM gives more reliable estimation of sensor offset as shown in Fig.9. Moreover, the sensor offset from LSM forms a sine wave due to the fixed polytropic coefficient value 1.32. Besides, the residual error of least-squares fitting of three methods are plotted in Fig.10.

Table 1, Table 2 and Table 3 summarizes the mean and standard deviation of polytropic coefficient estimation error, sensor offset estimation error, and residual error of least-squares fitting, respectively, for three pressure pegging methods. These statistical characteristics of parameter estimation errors are calculated for the adjacent simulated 2000 engine cycles. It is obvious that the LSM has a poor performance suffering from the assumption of an invariant polytropic coefficient value for all engine cycles. The mean values of polytropic coefficient estimation error and sensor offset estimation error from NLSM are most closed to zero, however, suffering from severe oscillations. It can be concluded that the polytropic coefficient and sensor offset simultaneous estimation is very sensitive to the sensor noise. The proposed $\kappa$CL-LSM obtains the most stable estimation of polytropic coefficient and sensor offset, and acceptable mean estimation errors. As a result of the low-pass feature of $\kappa$CL-LSM, the mean estimation errors are slightly larger than errors from NLSM. Moreover, for the residual error of least-squares fitting, NLSM achieves the best statistical characteristics. This is because of the relationship:

$$J_s(\kappa^*, p^\omega^*) \leq J_s(\kappa_{i-1}, p^\omega^*)$$  \hspace{1cm} (24)

where the equality holds only if $\kappa_{i-1} = \kappa^*$.

![Image of comparison](image)

**Fig.7 The effect of step size on parameter estimation in $\kappa$CL-LSM**

![Image of comparison](image)

**Fig.8 Estimated polytropic coefficient for simulated measured pressure data**

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5. Experimental Results

The mentioned three pressure pegging methods are tested on a 6-cylinder 3.5-liter Toyota spark-ignited engine that coupled with a dynamometer, as shown in Fig.11. The configuration of the test bench is shown in Fig.12. Kistler 6052CU20 pressure sensors in the fifth and sixth cylinders, a Kistler 2361B1 encoder on crankshaft and a Kistler 6054C12 charge amplifier are available for in-cylinder pressure collection, which acquisition accuracy is 1 degree. It should be noted that the amplifier gain or calibration factor, which indicates the relationship between the mechanical quantity and the corresponding voltage signal, is calculated internally and be set to 10 by system itself. The error of amplifier gain is within ±0.1% at 25°C. The effect of the variation in the amplifier gain has not been considered in this study. Pressure pegging methods are programmed in MATLAB/Simulink, and after be complied it can be downloaded into dSPACE equipment, so that the sensor offset and polytropic coefficient can be estimated in real-time.

Experiments have been firstly conducted at the motored condition: engine speed is 1200 rpm, throttle angle is 16 degrees, water temperature is 58 ~ 60 °C, oil temperature is 60 ~ 65 °C, room temperature is 28 ~ 32 °C. The collected motored pressure signals of 1000 adjacent engine cycles are plotted in Fig.13. The corresponding polytropic coefficient and pressure offset estimated by NLSM and CL-LSM are plotted in Fig.14 and Fig.15. At motored condition, the stochasticity of combustion disappears and the disturbances on gas state during compression stroke can be ignored. Hence, the polytropic coefficient of gas at motored condition can be considered as that of air. Moreover, the pressure offset shown in Fig.15 is also a constant, while the small oscillation is caused by the sensor noise. The result comparisons prove that CL-LSM can estimate polytropic coefficient and pressure offset effectively with small oscillations, while NLSM gives estimations with severe oscillations.

Table 1 Polytropic coefficient estimation error.

|       | LSM     | NLSM    | CL-LSM |
|-------|---------|---------|--------|
| Mean  | -       | 0.9415e-4 | 1.7022e-4 |
| S.D.  | -       | 0.0265  | 0.0075 |

Table 2 Sensor offset estimation error.

|       | LSM     | NLSM    | CL-LSM |
|-------|---------|---------|--------|
| Mean  | 0.0028  | 0.5063e-4 | -4.5899e-4 |
| S.D.  | 0.0606  | 0.0454  | 0.0154 |

Table 3 Residual error of least-squares fitting.

|       | LSM     | NLSM    | CL-LSM |
|-------|---------|---------|--------|
| Mean  | 0.0550  | 0.0524  | 0.0534 |
| S.D.  | 0.0102  | 0.0098  | 0.0099 |
dead center, water temperature is 75 ~ 78 °C, oil temperature is 65 ~ 70 °C, room temperature is 28 ~ 32 °C. The collected initial pressure signals of 1000 adjacent engine cycles are plotted in Fig.16. The comparisons of the mentioned three methods for the same group of experimental pressure data are illustrated in Fig.17 and Fig.18. As shown in Fig.17, both of the polytropic coefficient traces estimated by NLSM and CL-LSM scatter around 1.30~1.34. The value from NLSM has severe oscillation, while the value from CL-LSM is more stable. The sensor offsets evaluated by NLSM and CL-LSM also have similar characteristics, i.e., CL-LSM gives more reliable and stable estimation of sensor offset as shown in Fig.18.
6. Conclusion

In-cylinder pressure pegging is significant for pressure based combustion analysis and engine control. This paper proposed a polytropic coefficient cyclic learning least-squares method (CL-LSM) to evaluate the sensor offset and simultaneously consider the cyclic variation of polytropic coefficient. A comparative study of the least-squares method (LSM) with fixed polytropic coefficient, nonlinear least-squares method (NLSM) with a variable polytropic coefficient, and the proposed method is conducted using both the simulated pressure data and the experimental pressure data collected on a gasoline engine targeted in this research. The simulated and experimental results show that LSM has poor performance suffering from the assumption of fixed polytropic coefficient, estimations by NLSM have severe oscillations due the sensitivity to sensor noise, estimations by CL-LSM are more stable and reliable. Moreover, CL-LSM balances the computational cost and calculation precision. It’s possible to be used for pressure pegging and online polytropic coefficient estimation which might be of interest for $\Delta p$ method based trapped mass estimation.

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