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Mass Air Flow Sensor Diagnostics for Adaptive Fueling Control of Internal Combustion Engines

Patrick J. Buehler, Matthew A. Franchek
Purdue University
School of Mechanical Engineering
1077 Ray W. Herrick Laboratories
West Lafayette, IN 47907 USA
email: franchek@ecn.purdue.edu
Imad Makki
Ford Motor Company
Advanced Powertrain Control Systems
FPC-B, MD37
760 Towncenter Dr.
Dearborn, MI 48126 USA

Abstract

Presented in this paper is an information synthesis (IS) approach for the mass air flow (MAF) sensor diagnosis on internal combustion engines. An information synthesis solution is attractive for diagnostics since the algorithm automatically calibrates itself, reduces the number of false detections and compresses a large amount of engine health information into the model coefficients. There are three primary parts to information synthesis diagnostics. First, an IS model is used to predict the MAF sensor output based on the engine operating condition. The inputs to this IS model include the throttle position sensor (TPS) and the engine speed sensor information. The second part concerns an adaptation process that is used to reduce the errors between the IS model output and the actual MAF sensor output. Finally the adapted model coefficients are used to diagnose the sensor as well as identify the source for changes in the sensor characteristics. This proposed solution is experimentally tested and validated on a Ford 4.6 L V-8 fuel injected engine. The specific MAF sensor faults to be identified include sensor bias and a leak in the intake manifold.

1 Introduction

Owing to stringent governmental tailpipe emission regulations, the precise control of engine fueling has received considerable attention within the control community. Essentially the challenge in engine fueling control is the coordination of air and fuel entrainment into the engine cylinders [1].

Traditionally, the fueling control systems on today's production engines operate in a reactive mode. The driver input directly moves the throttle plate thereby immediately changing the air flow to the engine cylinders. A measurement of the air flow is accomplished using either a mass-air flow (MAF) sensor or manifold air pressure (MAP) sensor. From this air flow measurement, the fueling controller estimates the amount of air to be ingested into the cylinder on the next power stroke. Based on this air mass estimate and knowing the desired air fuel ratio that meets the emission requirements, the fueling control system calculates the necessary amount of fuel to be injected. Using this mass of fuel and measuring the injector characteristics a priori, the fueling controller is able to determine the needed injector pulsewidth command. An extensive literature base exists concerning the various ways in which the mass-of-air and mass-of-fueling estimates can be made and used in the fueling control system. [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15].

Whether or not the injector pulsewidth was correct can only be ascertained after-the-fact. This measurement is accomplished by the exhaust gas oxygen (EGO) sensor located in the exhaust manifold. This sensor measures the air/fuel ratio and can provide information as to whether there was too much fuel (rich condition) or not enough fuel (lean condition) injected. However this information only comes after the combustion event and has an associated transport lag.

Unfortunately, the source for the fueling error is not necessarily identified. Specifically, the injector pulsewidth command is based on many estimates concerning in cylinder air charge and in cylinder mass of fuel delivered. In reality, neither of these quantities are measured. Therefore, the incorrect estimate(s) within the fueling controller and the reason(s) for the estimation error(s) cannot in general be ascertained using only the EGO sensor. This lack of information has made the adaptive feedforward fueling control problem extremely difficult since root cause(s) leading

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to fueling control adaptation for fueling errors are elusive. Hence a diagnostic approach is necessary to identify the root cause of these errors.

Most of the current engine diagnostic approaches can be grouped into two categories. The first approach considers methods of fault detection based on the signature of a measured signal. Most of this engine diagnostic work in the literature deals with knock and misfire detection. Moskwa et al. [16] employs the crankshaft speed sensor output to monitor the work output of each cylinder. Ceccarani et al. [17] detects engine misfire by monitoring the exhaust gas pressure sensor in the frequency domain. Rizzoni and Lee [18] evaluate various misfire detection indices based on the measurement of the crankshaft angular velocity. Although these approaches detect faults successfully with extensive calibration, using only the signature of a sensor signal may lead to false fault detections and/or incorrectly diagnosed faults. The second fundamental approach considers methods that utilize observer theory to diagnose and identify faults. Laukonen et al. [19] concentrate on actuator and sensor calibration faults via fuzzy identification. Gertler et al. [20] use parity equations to identify specific sensor and actuator faults. Kao and Moskwa [21] propose the use of nonlinear observers to detect misfire. Kerns et al. [22] compare three different estimates of the airflow to identify faults. These methods are successful approaches to fault identification, however they are limited to identifying sensor specific faults and do not account for engine aging. Also model identification for these methods can be a significant task.

The work in this paper presents a model development approach that adapts a single air path model online, and monitors the evolution of the model coefficients to diagnose and identify the root cause of the MAF sensor error.

The application of this work is to identify which of the two estimates, mass-of-air or mass-of-fuel, were incorrect. For this work it will be assumed that at any one time, only one of the estimates is significantly inaccurate. This goal leads to the evaluation of the MAF sensor and its ability to measure the mass-air-flow into the engine intake manifold. This allows the diagnostic of specific engine faults in the air path. The two specific faults sought for detection are sensor bias (due to contamination) and intake manifold leaks.

The diagnostics method presented is outlined in Section 2. The method for development of the steady state MAF IS model is detailed in Section 2.1. The approach is demonstrated on a Ford V8 engine. Section 2.2 describes the MAF IS model parameter identification approach and experimental engine results are included. The details of fault identification, namely a leak in the engines air path and bias MAF sensor, is described in Section 2.3. Future research is detailed in section 2.4, including a proposed algorithm for online implementation of this procedure. Finally, the conclusions are included in Section 3.

2 Main Results

An information synthesis (IS) approach of the mass air flow sensor diagnostic problem is developed. The two specific MAF sensor faults to be identified are sensor bias and intake manifold leaks. Both of these two common faults will lead to an inaccurate measurement of the mass air flow. These faults can be identified during *steady state* operation of the engine. Therefore, a steady state IS model will be developed to predict the output of the MAF sensor. The input to this IS model will be the throttle position sensor (TPS) and the engine speed sensor.

There are three primary steps to the approach. First, a steady state IS model (in polynomial form) will be identified. This identification process includes the determination of the polynomial structure and the appropriate coefficients. The second step involves the adaptation of the steady state model. In the final step, the adapted model coefficients will be processed to determine the status of the MAF. Each of these three steps will be detailed in the following sections along with an experimental study.

2.1 Development of the Steady State MAF IS Model

Presented in this section is the steady state IS model development. The selected inputs for this model are the throttle position and engine speed. Throttle position is an obvious choice for the model input since the amount of air flow into the engine cylinders is greatly influenced by the throttle plate angle. However, for a given throttle position one of two possible air flow conditions over the throttle plate can exist, chocked or unchocked flow. To determine which flow condition exists, the engine speed sensor can be used.

Given these two inputs, one output, and an assumed polynomial structure for the steady state IS model, the resulting equation is

$$V_{MAF} = \sum_{i,j=0}^{\infty} c_{i,j} V_{RPM}^{i} V_{TPS}^{j}, \tag{1}$$

where V_{MAF} is the MAF sensor output voltage, $c_{i,j}$'s are the coefficients, V_{RPM} is the engine speed sensor voltage, and V_{TPS} is the TPS voltage. For reasons of implementation, the infinite series model in (1) will be truncated. The price paid for truncating (1) is a reduction in model accuracy.

To identify the significant regressors in (1) needed for the truncated IS model, a frequency based approach will be used. Specifically, each input will be comprised of a bias term (since the engine will be operating) and a single distinct excitation frequency. Analyzing the power spectral density (PSD) of the MAF sensor steady state output will reveal the significant regressors. Building the truncated model will be an iterative process. In particular, those regressors that produced frequencies in the PSD with large amplitudes will begin the IS truncated model. If the model accuracy is not satisfactory, additional regressors will be included and chosen based on the amplitude of the corresponding frequencies.

Regressors Identification for a MISO Nonlinear Static Model

A frequency domain approach is proposed to identify the significant regressors in (1) for the truncated IS model. The development begins by letting the inputs be

$$V_{RPM} = \bar{V}_{RPM} + A\ \sin(\Omega t) \tag{2}$$

and

$$V_{TPS} = \bar{V}_{TPS} + B\ \sin(\Phi t) \tag{3}$$

where the $\bar{()}$ denotes the nominal values in both throttle position and engine speed (in volts). To identify the regressors, the steady state output of the MAF sensor due to (2) and (3) will be analyzed. In particular, the PSD of the steady state MAF sensor output due to these sinusoidal inputs will be used to identify the significant terms needed for the truncated IS model.

Consider rewriting (1) as

$$\begin{aligned} V_{MAF} &= \textstyle\sum_{i=1}^{\infty} c_{i,0} V_{RPM}^{i} + \sum_{i=1}^{\infty} c_{0,i} V_{TPS}^{i} \\ &\quad + \textstyle\sum_{\substack{i=1,j=1\\ i=j=0}}^{\infty} c_{i,j} V_{RPM}^{i} V_{TPS}^{j} \end{aligned} \tag{4}$$

To determine an appropriate truncated form for the first two summations in (4), consider a polynomial having the form

$$y(t) = a_1 x(t) + a_2 x^2(t) + a_3 x^3(t) + \cdots$$

where the input is $x(t) = \bar{X} + A\sin(\Omega t)$.

It can be shown that the corresponding $y(t)$ is

$$y(t) = \bar{Y} + c_{1,0}\sin(\Omega t) + c_{2,0}\cos(2\Omega t) + c_{3,0}\sin(3\Omega t) + \cdots \tag{5}$$

The coefficient notation in (5) parallels that in (1) where the second input is constant. From (5), the regressors in (4) that significantly contribute to model accuracy and which are solely integer powers of the input(s) produce frequency components contained in $y(t)$ at the corresponding integer multiples of the input frequency Ω.

For the remaining summation in (4), the input cross-product terms will be identified in a similar manner. The structure of this polynomial is

$$\begin{aligned} y(t) &= a_{1,1}x(t)u(t) + a_{2,1}x^2(t)u(t) + a_{3,1}x^3(t)u(t) + \cdots \\ &\quad + a_{2,2}x^2(t)u^2(t) + \cdots \end{aligned}$$

where the inputs are

$$x(t) = \bar{X} + A\sin(\Omega t), \quad u(t) = \bar{U} + B\sin(\Psi t)$$

and $\Omega \neq \Psi$. The resulting $y(t)$ has the following structure

$$\begin{aligned} y(t) &= \bar{Y} + c_{1,1}^{-}\cos[(\Omega-\Psi)t] + c_{1,1}^{+}\cos[(\Omega+\Psi)t] \\ &\quad + c_{2,1}^{-}\sin[(2\Omega-\Psi)t] + c_{2,1}^{+}\sin[(2\Omega+\Psi)t] \\ &\quad + c_{3,1}^{-}\cos[(3\Omega-\Psi)t] + c_{3,1}^{+}\cos[(3\Omega+\Psi)t] + \cdots \\ &\quad + c_{2,2}^{-}\cos[(2\Omega-2\Psi)t] + c_{2,2}^{+}\cos[(2\Omega+2\Psi)t] \\ &\quad + \cdots \end{aligned} \tag{6}$$

From (6), the regressors in (4) that significantly contribute to model accuracy and which are cross product integer powers of the inputs produce frequency components contained in $y(t)$ at frequencies that are the sum and difference of the frequencies multiplied by the integer powers. That is, the $x^2(t)u(t)$ term produces the frequency components $(2\Omega+\Psi)$ and $(2\Omega-\Psi)$ in the output $y(t)$.

MAF IS Model for a Ford 4.6 L V-8 Engine

The proposed procedure will be used to obtain the truncated MAF IS model of the Ford 4.6L V-8 fuel injected engine maintained in the Purdue Engine Research Facility/Engine Control Technology Laboratory. Both throttle position and engine speed signals serve as the MAF IS model inputs. The engine throttle was perturbated at a frequency of 10 rad/sec (via a Jordan throttle controller) and the engine speed was perturbated at a frequency of 6 rad/sec (via an eddy current dynamometer). The resulting PSD of the MAF sensor voltage is shown in Figures 1, 2 and 3.

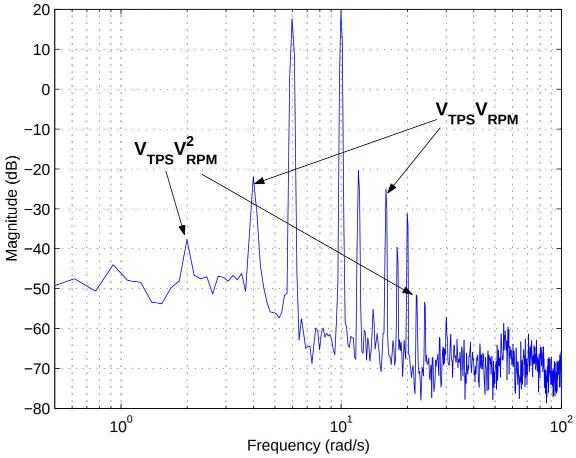

Figure 1: Power Spectral Density of the MAF Sensor Output with 6 and 10 rad/s Sine Wave Excitation to RPM and TP, respectively.

From Figures 1, 2 and 3 the initial regressors for the IS model are chosen to be

$$\begin{aligned} V_{MAF} &= c_{0,0} + c_{0,1}V_{TPS} + c_{0,2}V_{TPS}^2 + c_{0,3}V_{TPS}^3 \\ &\quad + c_{1,0}V_{RPM} + c_{1,1}V_{TPS}V_{RPM} \end{aligned}$$

2.2 MAF IS Model Identification

To identify the coefficients in the truncated IS model, a least squares approach will be used [23]. Since the model is a steady state model, long data lengths at a particular operating point can be averaged to reduce the bias in the coefficient estimates due to sensor noise. The engine speed/load conditions used to populate the information matrix of the least squares process is based on the drive cycle for the Federal Test Procedure (FTP) [24]. Shown in Figure 4 are the 106 speed/load combinations used for model identification.

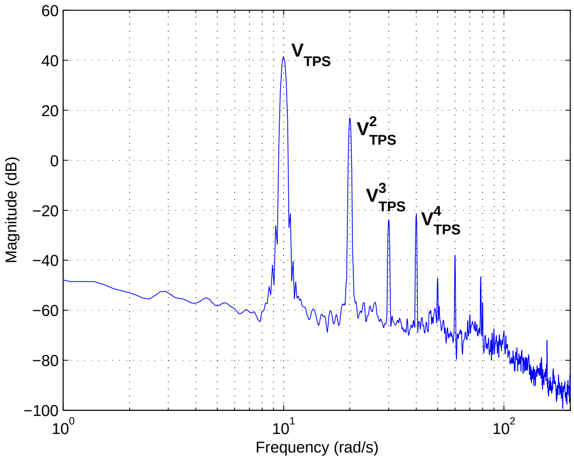

Figure 2: Power Spectral Density of MAF Sensor Output holding RPM Constant with a 10 rad/s Sine Wave Excitation to TPS.

The resulting truncated IS model is

$$\begin{aligned} V_{MAF} &= -5.27 + 10.02V_{TPS} - 4.54V^2_{TPS} + 0.625V^3_{TPS} \\ &\quad -0.225V_{RPM} + 0.247V_{TPS}V_{RPM} \end{aligned} \tag{7}$$

Shown in Figure 5 is the output of the IS model. The engine was loaded at various torques while the throttle was perturbed. The mean value of the absolute error over the entire operating range is 1.2% with a standard deviation of 1.3% and a maximum error of 6%. The error can be further reduced by adding the regressors associated with the next largest amplitudes in Figures 1, 2 and 3. Adding V^4_{TPS}, V^2_{RPM}, and $V_{TPS}V^2_{RPM}$ to the model reduce the mean value of the absolute value of the error to 0.5% with a standard deviation of 0.3%. The resulting model is

$$\begin{aligned} V_{MAF} &= -14.98 + 35.18V_{TPS} - 25.73V^2_{TPS} + 7.98V^3_{TPS} \\ &\quad -0.920V^4_{TPS} - 1.67V_{RPM} + 0.256V^2_{RPM} \\ &\quad +0.984V_{TPS}V_{RPM} - 0.130V_{TPS}V^2_{RPM} \end{aligned}$$

2.3 Mapping Faults to the MAF IS Model Coefficients

The faults introduced to the MAF sensor include a leak in the intake air path and a bias in the MAF sensor. An illustration of how these faults impact the MAF sensor output is shown in Figure 6. In particular, the data in Figure 6 was generated by holding the engine speed at 2000 rpm (via an engine eddy current dynamometer) while slowly increasing the throttle.

Retesting the 106 speed/load points from the FTP cycle with each fault introduced leads to the MAF IS model coefficients summarized in Table 1. The mean value of the error over the entire operating range for the bias and leak fault models are 1.2% with a standard deviation of 1.6% and a maximum error of 6% and 1.2% with a standard deviation of 1.8% and a maximum error of 6%, respectively. In these two cases there are specific patterns in the MAF IS model coefficients associated with each engine fault. It appears these patterns in the evolution of the model coefficients can be used to distinguish between the two faults. When the MAF sensor output contains a bias (10% in this case), all the coefficients are changed by essentially the same percentage. Alternatively, when a leak is introduced in the air path, the coefficients associated with V_{RPM} significantly change. The premise for this trend is that at a given TP, the amount of air being ingested through the leak is dependent on the pressure difference between atmospheric pressure and the intake air pressure. The pressure in the intake is governed by the engine speed (for a given TP). Hence, the coefficients associated with V_{RPM} significantly change.

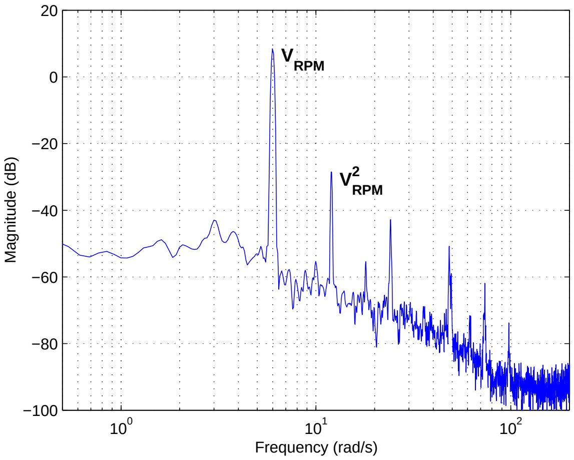

Figure 3: Power Spectral Density of MAF Sensor Output holding TPS Constant with a 6 rad/s Sine Wave Excitation to RPM.

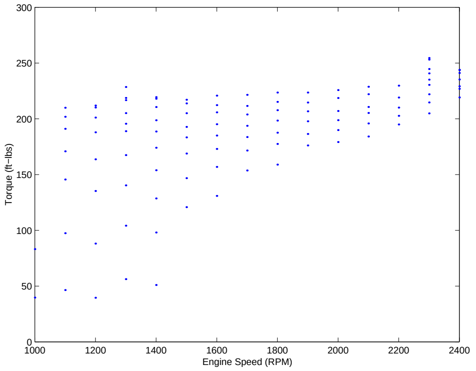

Figure 4: FTP Speed/Load Points.

2.4 Future Work

The proposed MAF IS model adaptation will follow the standard least squares approach [25]. However, there are two unique aspects of online identification associated with the IS model adaptation. First, the IS model adaptation is

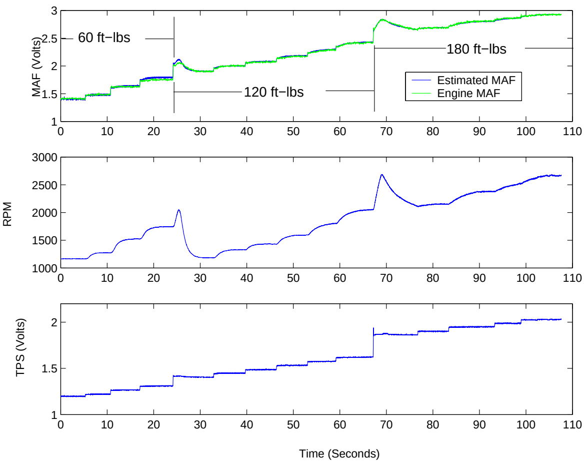

Figure 5: Model Verification.

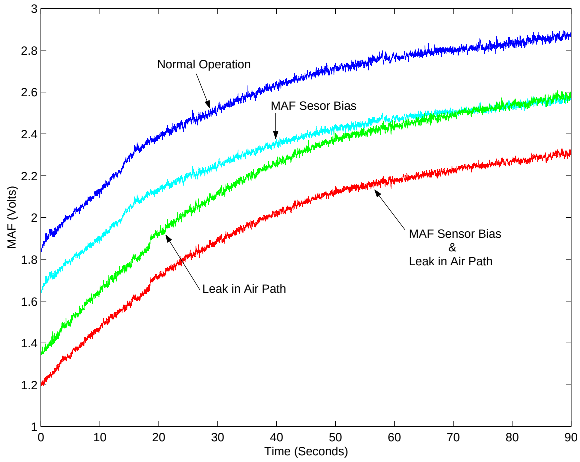

Figure 6: Effect of faults on the engine MAF for a constant speed of 2000 RPM.

only executed when a prespecified level of error exists between the IS model and the actual sensor output (in this case the MAF sensor output). Secondly, the IS model will only be adapted for the current operating point. The details of the adaptation process are presented herein.

As the steady state model accuracy degrades at a particular operating point denoted $(RPM^*, LOAD^*)$, online model adaptation will be used to recover accuracy. *However, the adaptation of* V_{MAF} *should be such that it changes only in the region about* $(RPM^*, LOAD^*)$. Therefore, the steady state model does not change at other locations where the model accuracy is either acceptable or unknown. The proposed steady state adaptive algorithm is:

1. Detecting the need for adaptation: The degradation of V_{MAF} will be detected from a *threshold condition* representing desired IS model accuracy.

Table 1: Model Coefficients for normal and fault engine operation

	Normal	Bias	% diff.	Leak	% diff.
$c_{0,0}$	-5.27	-4.71	10.6	-4.82	8.5
$c_{0,1}$	10.02	8.96	10.6	9.02	9.8
$c_{0,2}$	-4.54	-4.06	10.6	-4.06	10.6
$c_{0,3}$	0.625	0.559	10.5	0.559	10.5
$c_{1,0}$	-0.225	-0.202	10.3	-0.106	52.8
$c_{1,1}$	0.247	0.221	10.6	0.203	18.0

2. Formulating the Least Squares Adaptive Model Problem: To adapt the coefficients in (7) online, the problem will be formulated as a least squares problem. To begin, a library of information will be created using (7) by gridding the range of V_{TPS}, and V_{RPM} based on the FTP cycle. From (7), the following matrix can be calculated

$$\mathbf{V}_{MAF} = \mathbf{P}\,\Phi \tag{8}$$

where Φ contains the coefficients of (7) to be calculated, $\mathbf{V}_{MAF}$ is a vector of calculated mass air flow voltages from (7) before adaptation, and $\mathbf{P}$ is the corresponding matrix of the inputs and their cross terms. Each row in (8) corresponds to a particular speed/load combination in the library.
3. Incorporating the data obtained from the operating point $(RPM^*, LOAD^*)$**:** Substitute both RPM^* and $LOAD^*$ along with the measured V^*_{MAF} into (7). Let this equation replace the row in (8) for the load/speed combination which is closest to $(RPM^*, LOAD^*)$.
4. Solve for the coefficients using (9): The coefficients can be solved using a least squares formulation. From (8) and provided P^TP is invertable, the coefficients are

$$\Phi = (\mathbf{P}^T\mathbf{P})^{-1}\,\mathbf{P}^T\mathbf{V}_{MAF} \tag{9}$$

A recursive least squares formulation could also be utilized.

Comments: This passive adaptive formulation has very attractive online adaptation properties; the issue that $\mathbf{P}^T\mathbf{P}$ must be invertable in (9) is addressed. In particular, all the elements of $\mathbf{P}$ have come from (7) except for one row which is obtained from data where V_{MAF} is in error. Thus, this row will not be a linear combination of other rows. Furthermore, the model adaptation will be local as opposed to global. Consequently, V_{MAF} in (7) will be slowly adaptive.

3 Conclusions

Developed in this paper is an information synthesis approach to engine diagnostics. In particular, this work focused on the diagnosis of the MAF sensor used for engine fueling control. The goal of this work is to utilize systems level model identification (steady state models in this case), and online model adaptation for diagnostics. For the two MAF sensor faults considered in this experimental study, it was demonstrated that each lead to a unique change in the model coefficients. As a result, not only can the status of the MAF sensor output be evaluated, but the root cause for MAF degradation can also be captured.

4 Acknowledgment

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