

Ignition of Combustible Materials by Motor Vehicle Exhaust Systems - A Critical Review

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ABSTRACT

This paper summarizes hot surface ignition data for automotive fluids in the literature, as well as the ignition data for vegetation, paper and cotton, and compares it to measured motor vehicle exhaust system temperatures. While hot surface ignition is a complex phenomena and the temperatures attained by motor vehicle exhaust systems depend on many factors, these comparisons can be useful in evaluating motor vehicle fire causation scenarios. Comparing hot surface ignition data in the literature is complicated by limitations in the statistical analysis used to address the underlying probabilistic nature of the ignition data. Because the statistical uncertainty of measured ignition probability can be significant, this paper reviews the three methods that have been used to address this probabilistic nature in the literature and illustrates statistical techniques that can be used to make statistically significant comparisons between different sets of ignition data.

INTRODUCTION

Within the engine compartment of modern motor vehicles are a number of combustible materials necessary for proper performance of the engine and auxiliary systems. For a conventional internal combustion engine, these combustibles include the engine fuel, engine oil, transmission fluid, brake fluid, power steering fluid, engine coolant and windshield washer fluid. Internal combustion engine fuel types can include gasoline, diesel and a number of alternative fuels such as gasoline-ethanol blends or biodiesel.

Under normal circumstances, these combustibles are generally well removed from hot exhaust system components. However, unusual conditions or events such as faulty repair, improper maintenance, or a severe collision can result in these combustibles coming into contact with hot exhaust

system components. This paper summarizes and compares hot surface ignition data for automotive fluids in the literature to measured motor vehicle exhaust system temperatures. Since unintended fuel sources such as paper, vegetation and cotton rags could also come into contact with motor vehicle exhaust systems, the ignition data for these combustibles are also included in this comparison.

While the ignition characteristics of automotive fluids is complex, depending on many factors, comparison of ignition data in the literature is further complicated by the statistical analysis used to address the probabilistic nature of the ignition data. The probabilistic nature of the ignition data is associated with a temperature range over which the probability of ignition increases as the surface temperature increases. Because the uncertainty of the measured ignition can be significant and since most studies did not report the uncertainty of the reported results, this paper also reviews the three methods that have been used to address this statistical nature and the uncertainty associated with each.

LITERATURE REVIEW

The significant diversity of the hot surface ignition studies involving automotive fluids [1,2,3,4,5,6,7,8,9,10], including the types of fluids tested, the experimental set-up and the statistical approach used, is summarized in [Tables 1](#) and [2](#). Santrock and Kononen [1], Colwell and Reza [2] and Arndt et al. [3] all tested most of the common types of engine fuels, lubricants or oils, coolant, and windshield washer fluid, albeit with significantly different experimental set-ups. Santrock and Kononen [1] used a heated crucible as the test surface into which 25 ml of test fluid would be introduced for each test. As shown in [Table 1](#), this sample size was 10 times larger than all other reported sample sizes and was approximately 1000 times larger than the single drops used by Colwell and Reza [2]. Because of the large sample size, the fluid could boil within the crucible for a relatively long

time and ignition delay times could be on the order of several minutes. In addition to allowing for long ignition delay periods, it is also possible that these long boiling periods may have altered the chemical make-up of the remaining liquid in the crucible.

In the tests conducted by Colwell and Reza [2], a single drop of the test fluid was dropped onto a heated, horizontal, flat plate. Due to the relatively small liquid volume, heat transfer and the associated boiling of the drop caused relatively quick vaporization of the drop and, if ignition occurred, it was generally within approximately 1 second after contacting the plate. Using a significantly different experimental set-up, Arndt et al. [3] sprayed test fluids onto the vertical surface of a catalytic converter, although the characteristics of the spray were not described.

The other studies shown in [Table 1](#) exclusively involved motor vehicle fuels, with the exception of the study by Hull et al. [10] involving ethylene glycol. Similar to Colwell and Reza [2], tests conducted by Byers et al. [5] involved a single drop of gasoline that was dropped onto a horizontal flat plate. In this study, the effect of various types of surface materials was examined. LaPointe et al. [4] dropped multiple drops of gasoline onto various automotive manifolds and heat shields. Davis et al. [6] and Somandepalli et al. [7] both used the same experimental set-up, in which approximately 0.25 ml of fluid was injected into a recessed horizontal flat plate. While Davis et al. [6] tested gasoline, the Somandepalli et al. [7] study also involved various ethanol-gasoline blends and biodiesels. Ebersole et al. [8], using the same experimental set-up as Santrock and Kononen [1], also studied gasoline and various ethanol-gasoline blends. Severy et al. [9] tested both gasoline and diesel on a steel tube, but few other details are known about this experimental set-up. Hull et al. [10] tested only ethylene glycol on a heated steel tube. Battery acid, a sulfuric acid and water mixture, as well as R-134a refrigerant (CH_2FCF_3 - 1,1,1,2-tetrafluoroethane) are not included in the study as they are not flammable at atmospheric pressure [11-12].

For the purpose of comparing this data to measured motor vehicle exhaust system temperatures, the lowest temperature in which ignition occurred and the highest temperature at which ignition did not occur was extracted from each study for each fluid tested. Because the statistical approach associated with these studies varied considerably, this approach was the most consistent method for comparison purposes. When studies involved variations of the same fluid type, such as gasoline grade or engine oil brand or weight, the data for each fluid type was combined and then the lowest temperature for ignition and the highest non-ignition temperature were found for the combined data set. The same approach was used for the ignition characteristics of the same fluid on different test surfaces. The ignition temperature data

that was extracted using this approach represents the range of temperature where ignition was observed at the particular set of conditions associated with the test. As will be described in subsequent sections, comparisons of this type are dependent on the number of tests conducted and the temperature at which they were conducted. The low end of any particular ignition temperature range is not necessarily the lowest temperature for ignition for a given experimental set-up and fluid nor is the upper range necessarily the absolute maximum temperature at which ignition might not occur. For comparison purposes, the 10% and 90% ignition probability temperatures from Colwell and Reza [2] were used for the upper and lower temperature. For the antifreeze comparisons, the data from Santrock and Kononen [1] involved pure ethylene glycol and propylene glycol as well as these same fluids mixed in 1:1 ratios with water. Colwell and Reza [2] and Arndt et al. [3] both used pure antifreeze, but did not specify if it was propylene glycol or ethylene glycol, while Hull et al. [10] used ethylene glycol.

The exhaust system temperatures used for comparison to the ignition temperature ranges described above were taken from Colwell and Biswas [13] and Spreen et al. [14]. The Colwell and Biswas [13] study involved six test vehicles which were driven around a nominally level test track at speeds ranging from zero (idle) to 70 mph. For each test vehicle, thermocouples were welded to the exhaust manifolds and catalytic converters. This data is complemented with the data from Spreen et al. [14], who measured the surface temperature of catalytic converters in tests where the vehicle was driven on a dynamometer. While the catalytic converter data from Colwell and Biswas [13] was collected with vehicle speed induced airflow over the catalytic converters, the data from Spreen et al. [14] had no such vehicle speed induced airflow, although cooling fans were likely utilized.

Although numerous other motor vehicle exhaust system temperature studies have been conducted [15,16,17,18], these studies are confounded [19] by the use of hose clamps to mount the thermocouples to the exhaust system and the driving conditions of the tests. Results from Colwell and Biswas [13] have shown that the use of hose clamps to attach thermocouples to exhaust system temperatures not only leads to artificially low temperature measurements, it can also produce artificial transient temperature response, particularly when the vehicle is suddenly brought to rest and allowed to cool. Furthermore, these studies [15,16,17,18,19] describe changing vehicle speed to negotiate traffic and/or changes in road grade during the tests. Because internal combustion engines are not thermodynamically perfect [20] and must reject some heat to the environment, changes in engine load due to road grade or vehicle speed can result in higher exhaust system temperatures. However, changes in road grade and vehicle speed were not documented during the tests. As a result, it is unclear what effect changes in vehicle speed or road grade during these tests may have had on the

reported temperatures. The following section compares the exhaust system temperatures from Colwell and Biswas [13] and Spreen et al. [14] to the ignition data in the literature for automotive fluids, vegetation, paper and cotton.

COMPARISON OF IGNITION DATA TO MOTOR VEHICLE EXHAUST SYSTEM TEMPERATURES

Comparisons of the hot surface ignition data for engine oil, transmission fluid, brake fluid, power steering fluid, antifreeze, windshield washer fluid, diesel, gasoline, biodiesels and ethanol-gasoline blends to measured motor vehicle exhaust system temperatures are shown in [Figures 1,2,3,4,5,6,7,8,9](#). In these figures, the exhaust system temperatures from Colwell and Biswas [13] for the exhaust manifolds from 0 (idle) to 70 mph are shown on the right portion of the graph. For each of the six test vehicles, the temperature of the left and right manifold (if measured) is shown. On the left side of the plot are the ignition temperature ranges from each of the relevant studies described above. Also shown on these plots is the auto ignition temperature of the test fluid and the associated source for this data. Many of these auto ignition values were taken from NFPA 921 [21] and were originally compiled from material safety data sheets. One of the most common test protocols to determine the auto ignition temperature of a fluid is ASTM E-659 [22]. The auto ignition temperature for brake fluid is taken directly from material safety data sheets [23], as the value in NFPA 921 [21] is incorrect. If ignition was attempted but not achieved for a particular fluid, the highest temperature that was tested is plotted in the comparison plots with an upward pointing arrow above the symbol.

The hot surface ignition values for the fluids shown in [Figures 1,2,3,4,5,6,7,8,9](#) illustrate that the temperature required for hot surface ignition to occur is not a well-defined fluid property. Instead, as described previously by Colwell and Reza [2], the hot surface ignition temperature is strongly coupled to numerous factors, including the properties of the surface, the liquid spray or stream and the local airflow. Because of this coupling, the temperature required for ignition can vary widely. These comparisons are further complicated by the statistical approach used and the underlying probabilistic nature of the ignition data. As will be described later, these temperatures are dependent on how the tests were performed, particularly the number of tests conducted at various surface temperatures.

The ignition data for vegetation used for comparison to measured motor vehicle exhaust system temperatures was taken from a National Institute of Standards and Technology (NIST) study conducted by Pitts [24]. In this study, various types of vegetation were placed into a wire screen cage

nominally 10.2 cm × 10.2 cm and 2.5 cm thick. At the initiation of the test, a metal shutter at the bottom of the cage was removed so that the vegetation could come into contact with a 10.2 cm × 10.2 cm heated copper plate. In addition to vegetation, this study also tested the ignition characteristics of newspaper. A summary of the results from this study for the case of no wind is shown in [Figure 10](#). Consistent with the classic ignition delay curve observed with other combustible material [25], as the surface temperature of the plate increases, the time for ignition to occur decreases. The data is presented as time for glowing ignition to occur as it was found that, once glowing ignition occurred, transition to flaming combustion was common. As shown in these results, all of the time versus temperature curves for the vegetation types tested along with newspaper tended to fall within the same general range.

Additional data for the ignition of paper was taken from Graf [26], who tested a wide range of paper types, and Smith and King [27]. In the experimental set-up used by Graf [26], the temperature of heated air that was flowing over the surface of the paper samples was increased until ignition occurred. Smith and King [27] utilized radiant heat to ignite paper samples and measured the surface temperature of the paper just prior to ignition with a pyrometer. Ignition data for cotton was taken from Patten [28] and Pal and Macskasy [29], who both used ASTM D 1929 [30]. The comparison of the ignition data described above for vegetation, paper and cotton to the exhaust manifold data from Colwell and Biswas [13] is shown in [Figure 11](#).

Because vegetation, cotton rags and paper could all come into contact with underbody catalytic converters, this same ignition data is also compared to the catalytic converter data from Colwell and Biswas [13] and Spreen et al. [14] in [Figure 12](#). As described previously, in the Colwell and Biswas [13] study, the underbody catalytic converters were exposed to vehicle induced airflow while the catalytic converters from Spreen et al. [14] had no airflow as the tests were conducted on a dynamometer. However, engine cooling fans were likely used for this dynamometer testing.

STATISTICAL ANALYSIS OF HOT SURFACE IGNITION DATA

One of the important features of hot surface ignition data of liquid fuels and oils in the literature is a range of temperatures over which ignition is probabilistic in nature. Within this range, as temperature increases, the probability of ignition also increases. When drawing conclusions from hot surface ignition data or comparing different sets of ignition data to each other, utilizing a statistical analysis that properly accounts for this probabilistic behavior can be important. One method to address this probabilistic behavior and the associated uncertainty in ignition probability is to compute confidence intervals. If the confidence intervals from two sets

of data overlap, the difference between the data sets could be entirely attributed to statistical uncertainty with changes in independent variables such as fluid type, surface geometry, etc. potentially having no influence on the differences in the observed results.

In the following sections, the three common approaches used to present or process hot surface ignition data in the literature are reviewed and, where appropriate, techniques that can be used to determine the confidence intervals for ignition probability are presented. The first approach used in the literature was to conduct repeated ignition tests at the same or similar surface temperature from which the ignition probability is computed [5,6,7, 31]. The second approach was to perform a regression analysis on the entire set of ignition data, with the chosen form of regression being logistic regression [1-2, 6-7, 31]. In the third method, the lowest temperature to cause ignition and the highest temperature that did not cause ignition are reported [1, 3-4, 6,7,8,9, 31].

By utilizing the statistical techniques described below, the confidence intervals associated with some of the existing data in the literature can be computed and, as a result, statistically significant comparisons could then be made between some sets of ignition data. The statistical techniques presented here may also be useful in planning hot surface ignition studies where statistically significant comparisons from one set of ignition data to another are important.

IGNITION PROBABILITY COMPUTED AT CONSTANT TEMPERATURE OR A LIMITED TEMPERATURE RANGE

Many of the studies shown in Table 2 conducted between 5 and 10 ignition tests at a fixed surface temperature [1, 5,6,7,8, 31]. The results were then presented as the computed ignition probability, $\hat{p}$, versus surface temperature. With this type of testing, if all important independent parameters are held constant during each of these tests such that the ignition probability is the same for each test, the ignition probability density function is uniform. In this case, each of these tests is referred to as a Bernoulli trial and each group of 5-10 tests at a particular temperature is referred to as a simple random sample (SRS). Figure 13(a) shows a typical uniform probability density function when the ignition probability, p , is 0.2. If a large number of 10 trial samples (SRSs) were conducted and the number of observed ignition events, B , was recorded for each sample, the resulting distribution of the outcomes is described by a binomial distribution, which is shown in Figure 13(b). As shown in this figure, the most likely number of observed ignition events, or positive outcomes B , is 2. This is intuitive, as 2 ignitions in 10 trials gives a measured ignition probability, $\hat{p}$, of 0.2 ($\hat{p} = B/n = 2/10 = 0.2$). However, this only occurs in about 30% of the 10 sample trials. In the other approximately 70% of the samples,

a result other than 2 is observed and the computed ignition probability, $\hat{p}$ is at least 0.1 in error from the true ignition probability, p .

As the number of trials, n , in each SRS becomes large, the distribution of the outcomes can, according to the central limit theorem, be approximated by a normal distribution. If this is the case, the mean and standard deviation of the number of observed ignition events are np and $\sqrt{np(1-p)}$, respectively [32]. The computed probability, $\hat{p}$, based on the observed ignition events can also be approximated by a normal distribution, with the mean and standard deviation given by p and $\sqrt{np(1-p)}$, respectively [32]. However, Moore and McCabe [32] recommend that the normal distribution does not accurately describe the binomial distribution unless both $np \geq 10$ and $n(1-p) \geq 10$. In the above example where $p = 0.2$, the required number of trials in the constant temperature sample would need to be about 50 before the binomial distribution could be accurately represented by a normal distribution. It is clear from Figure 13(b) that the binomial distribution associated with 10 trial samples is not that of the bell-shaped curve of the normal distribution.

While a normal distribution cannot be used to estimate the uncertainty of measured ignition probability results for small sample sizes, Hollander and Wolfe [33], using more involved techniques, have tabulated confidence intervals for various small sample size binomial distributions. For a sample consisting of 10 ignition tests at a constant temperature (Bernoulli trials), the 95% confidence intervals are shown in Table 3. To illustrate these confidence intervals on measured hot surface ignition data, the 200 ignition tests involving gasoline from Colwell and Reza [2] were grouped into 20 samples (SRSs) that each consisted of 10 ignition tests. The tests from the original Colwell and Reza [2] study were collected at various temperatures with few tests conducted at the same temperature. For each of the 20 samples, which were conducted at approximately the same surface temperature, the ignition probability, $\hat{p}$, was computed and then plotted along with the 95% confidence intervals shown in Table 3. The results, shown in Figure 14, are compared to the logistic regression curve and the associated 95% confidence intervals as originally shown by the authors [2]. The logistic regression fit was shown to be very good with a P -value of 0.97, and the 95% confidence intervals at an ignition probability of 0.5 were 0.42 to 0.58 ($m = \pm 0.08$).

It is clear from Figure 14 that the uncertainty in the computed ignition probability from 10 trial samples is quite large. In fact, the confidence intervals for computed ignition probability span more than 0.5 in some cases. The confidence intervals shown in Table 3, or similar values from Hollander and Wolfe [33] for other sample sizes, can be directly applied

to the data in the literature that used this technique to present their results [5,6,7, 31] or for visual comparison to logistic regression fits [6-7, 31].

The range of the confidence intervals is important when comparing data from two experiments, such as comparing the results from one fluid to another or from one surface to another. If the confidence intervals of the data overlap, the difference could be attributed entirely to the uncertainty in the measurement such that the independent variable (i.e., fluid type or surface material) may have had no influence on the outcome. While the confidence intervals are large for 10 trial samples, the interval can be decreased by increasing the number of tests conducted in each sample. When the number of trials is large enough that the binomial distribution can be approximated by a normal distribution, the number of samples necessary to achieve a given confidence interval is given by [32]

$$n = \left(\frac{z^*}{m} \right)^2 p(1-p) \quad (1)$$

In this relationship, z^* is the standard normal distribution (1.960 for 95% confidence level) and m is the desired confidence interval on either side of the computed probability. To achieve a confidence interval similar to the confidence interval of the logistic regression curve shown in Figure 14, $m = \pm 0.08$, the number of trials in the sample associated with each ignition probability (or test temperature associated with this ignition probability) as computed from the above relationship is shown in Figure 15. If an average of 100 tests were necessary at each of the 20 temperature ranges, 2000 tests would be necessary to achieve the same confidence intervals as those associated with the logistic regression curve based on only 200 tests. This is one of the many advantages of logistic regression which will be described in more detail in the next section.

Logistic Regression

The second approach to treat the probabilistic nature of ignition data was to perform a regression analysis on all of the data in a particular data set. The regression form used was that of logistic regression as shown below.

$$\text{Ignition Probability} = \hat{\pi} = \frac{\exp(b_0 + b_1 X)}{1 + \exp(b_0 + b_1 X)} \quad (2)$$

In the case of hot surface ignition data, X is the surface temperature and $\hat{\pi}$ is the ignition probability as computed from the logistic regression equation. The values of the coefficients b_0 and b_1 are determined by maximizing the log-likelihood function below [34, 35].

$$\log_e L(\beta_0, \beta_1) = \sum_{i=1}^n Y_i(\beta_0 + \beta_1 X_i) - \sum_{i=1}^n \log_e [1 + \exp(\beta_0 + \beta_1 X_i)] \quad (3)$$

When the log-likelihood function is maximized, $\beta_0 = b_0$ and $\beta_1 = b_1$. In this relationship, n is the number of ignition tests in the data set, X_i is the temperature for each test, and Y_i is the outcome, 1 for ignition and 0 for no ignition. There is no closed-form solution to determine the coefficients b_0 and b_1 , so computer-based numerical routines are used to determine these values. As with any regression analysis, once the coefficients b_0 and b_1 have been determined for a particular set of ignition data, the fit needs to be evaluated. This is analogous to evaluating the R^2 value for a linear regression analysis. If the fit is poor, regression using a different regression form should be explored or the regression analysis should be abandoned entirely.

In linear regression, a plot comparing the results of the regression analysis and the actual measured value can be very useful in evaluating the fit. With this type of scatter plot, deviations from linear behavior by the data in general, or by individual data points, are often clearly evident. With logistic regression, however, the Y values of data can take on only two values, 0 or 1, and assessing the fit is not intuitive. While the fit can be examined visually by plotting $\hat{p}$ as a function of temperature, as described in previous sections, the uncertainty in the computed probability values can be quite large, which can minimize the value of this approach. For example, if the measured probability was 0.2 from a 10 trial sample, the error associated with that measurement (95% confidence intervals) could be 178%. Because there can be considerable uncertainty with each individual data point, assessing the curve fit visually is problematic, although several authors have attempted to evaluate goodness-of-fit using this approach [6-7, 31]. As a result, formal goodness-of-fit tests are often required to ensure that the data is well represented by the logistic regression form.

One of the methods that can be used to evaluate a logistic regression fit is the formal chi-square goodness-of-fit test [34-35]. In this test, the ignition results are broken up into a number of temperature or probability ranges. Within each temperature range, the number of ignition events expected based on the logistic regression curve is computed from

$$E_{j1} = \sum_{i=1}^l \hat{\pi}_i \quad (4)$$

where $\hat{\pi}_i$ is the computed ignition probability for each test, i , l is the number of tests in each range, and j indicates which range in which the expected value is being computed; j varies from 1 up to the total number of temperature ranges used.

The expected number of non-ignition cases is the total number of tests in that probability range minus the number of expected ignition events.

$$E_{j0} = I_j - E_{j1} \quad (5)$$

The observed ignition, O_{j1} , and non-ignition events, O_{j0} , are the experimentally observed results of the tests for each temperature range or class. The test statistic of interest for the chi-squared goodness-of-fit test is

$$\chi^2 = \underbrace{\sum_{j=1}^c \frac{(O_{j1} - E_{j1})^2}{E_{j1}}}_{\text{Ignition Events}} + \underbrace{\sum_{j=1}^c \frac{(O_{j0} - E_{j0})^2}{E_{j0}}}_{\text{No Ignition Events}} \quad (6)$$

The first term in this relationship is the difference between the expected and observed ignition events in each class, which is then squared and divided by the expected number of ignitions, which is then summed for each of the temperature ranges. The second term is similar but for the no ignition cases. If the fit is perfect, the expected and observed ignitions in each class will be the same. As a result, the expected and observed no ignition cases would also be the same and the χ^2 statistic would be 0. The number of degrees of freedom of the χ^2 statistic is the difference between the number of classes and the number of coefficients (2 in this case for regression with b_0 and b_1). If 6 temperature ranges ($c = 6$) are used, the number of degrees of freedom are $c - 2 = 4$. Once χ^2 is determined, it can be used to compute the P -value. The P -value is the area underneath the chi-squared distribution to the right of the computed χ^2 test statistic. If the χ^2 statistic were to be zero, the P -value would be 1, indicative of an excellent fit. For gasoline from Colwell and Reza [2], the χ^2 statistic was 0.57. The P -value is $P\{\chi^2(4) > 0.57\} = 0.97$. So, only 3% of the area is to the left of the χ^2 statistic with 97% of the area to the right and the fit is very good. If the χ^2 test statistic was such that the area under the curve to the right of χ^2 were only from about 0 to 0.1 (P -value of 0 - 0.1), the fit is poor and should not be used.

One of the difficulties of using the chi-squared goodness-of-fit test is satisfying the requirements of the test. Hosmer and Lemeshow [35] recommend that at least six classes be used. Using less than six classes can produce erroneous results as the test will almost always indicate a good fit. Furthermore, the expected number of ignition and non-ignition events in each class should generally be larger than 5. This requirement can be problematic, especially for data sets consisting of 200 data points or less. One method that can be used to help satisfy this requirement is to collect ignition data in the center

of the probabilistic temperature range as opposed to the tails. This shrinks the width of the probability classes in the center of the range and extends the probability ranges at the tails of the probability curve, making it easier to satisfy the requirement of having at least 5 expected ignition and no ignition events in each class. This is somewhat counterintuitive since other methods are focused on determining the lowest temperature for ignition and the highest non-ignition temperature and, therefore, tend to place emphasis on data at both tails of the curve. Note that the ignition data from Colwell and Reza [2] for gasoline shown in Figure 14 is primarily in the center of the probabilistic range with less data at the tails.

Some investigators [6-7, 31] have described their experimentally measured ignition probability curves as a function of temperature as being “skewed S-curves”. These investigators stated that “Almost all the fuels exhibit a similar behavior of a longer ‘tail’ of low ignition probability and a sharper definition of the temperature for high ignition probability” [6]. Because the logistic regression form must be symmetric about the 50% ignition probability point, it is unlikely that logistic regression will be appropriate for this data. In Somandepalli et al. [7], the authors found that only 2 of 7 sets of ignition data fit the logistic regression form well, although the requirement for expected frequencies being greater than 5 was not met for 5 expected values which can produce artificially good fit results [35], as described above. In Davis et al. [6] and Davis et al. [31], formal goodness-of-fit tests were not performed such that the quality of the fit is unknown. Since the shape of the ignition curve described is inconsistent with the logistic regression form and a formal goodness-of-fit was not performed, the computed ignition probability and associated conclusions based on these regression fits in these studies should be interpreted with care.

If the logistic regression fit is good, one of the significant advantages of using this approach is that powerful inference and diagnostic techniques which parallel those for linear regression can be used. This includes determining the confidence intervals for any given value of temperature along the ignition probability curve. To compute the confidence intervals for regression involving two coefficients [34], the Hessian matrix is computed from derivatives of the log likelihood function shown in Equation 3.

$$\mathbf{G}_{2 \times 2} = \begin{bmatrix} g_{ij} \end{bmatrix} \quad i = 0, 1; j = 0, 1 \quad (7)$$