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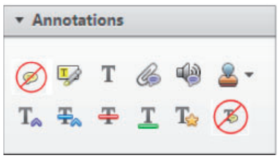

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On the accuracy of the assessment of open-air pressure loads due to passing trains: Part I: Experimental assessment

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Abstract

Passing trains generate aerodynamic loads ('open-air pressure pulses') that cause fatigue on wayside objects and other trains. The European regulatory framework requires, for every rolling stock type, type tests in which the peak-to-peak pressure changes caused by passing trains are measured close to the track over a range of heights. These measurements are subsequently corrected and processed so as to obtain an assessment value, which is then compared with a limit value. The assessment value is characterized by uncertainty. In this paper, we provide quantitative indicators of such uncertainty based on work carried out in the European FP7 project AeroTRAIN.

Keywords

Train aerodynamics, train pressure pulses, uncertainty analysis, virtual acceptance, TSI

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Introduction

Passing trains generate aerodynamic loads ('open-air pressure pulses') that cause fatigue on wayside objects and other trains. The loads are due to pressure changes that are mainly located at the head and tail of the train and at the coupling zone in the case of coupled trains. In order to limit such aerodynamic loads, the European regulatory framework[1–3] requires, for every rolling stock type, type tests in which the pressure changes Δp caused by passing trains are measured in the open air and processed so as to obtain an assessment value, which is then compared with a limit value.

According to the rolling stock Technical Specifications for Interoperability (TSI)[1,2], the pressure changes Δp must be measured at a specified lateral distance from the track and at seven different specified heights above the top of rail (TOR). Figure 1 illustrates the main features of the experimental setup: probes for pressure measurement and an example of the signals measured by one of the probes. In such a signal, the rapid and important changes due to the passage of the head and tail of the train are visible, along with smaller peaks associated with the passage of each coach composing the train. The maximum peak-to-peak variation Δp of the time signal is taken, and corrected for measured train speed and air density (Δp_c). This pressure change varies over the prescribed range of heights; its maximum value over such heights is taken as the characteristic value Δp_{ci} for train passage i. A sample of at least 10 train passages, at a measured ambient wind speed below 2 m/s, is required to form the assessment value

$$\Delta p_{2s} = m + 2s \tag{1}$$

where m is the mean value of the sample and s is its standard deviation.

This assessment value is characterized by uncertainty. A framework for expressing this uncertainty was developed for the research projects 'TrioTRAIN', funded under the European Commission's Seventh Framework Programme.[4] The TrioTRAIN Uncertainty Framework consists of: definitions; methods; objects of analysis; variables; and references. For the purposes of this paper, we now summarize the most useful concepts. Other concepts will become apparent in course of this paper.

The main definition is that of assessment uncertainty itself. It is acknowledged that no single figure can be provided using current state-of-the-art approaches. It is therefore represented by indicators,

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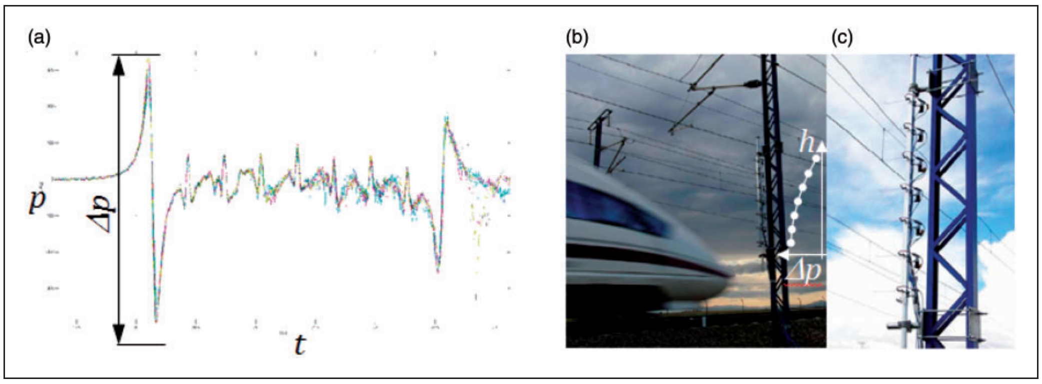

Figure 1. Illustration of experimental setup for the measurement of pressure changes: (a) example of a measured signal; (b) train passing an instrumented mast (note the variation of the pressure change over the range of seven heights above TOR); and (c) close-up of the mast equipped with probes.

as will be seen in this paper. Two types of indicators are used: indicators of precision and indicators of trueness. In order for an assessment process to be of high accuracy (i.e. to have a low assessment uncertainty) it has to be both of high precision and of high trueness. Precision of an assessment indicates that, if repeated many times for the same rolling stock type, it leads to assessment values that lie within a narrow range (i.e. the assessment has a good repeatability and reproducibility). Trueness of an assessment indicates the closeness of the assessment value to a true value, usually proven by comparing the results (when available) of different independent assessment tools taken as a reference point. Typical demonstrations of trueness occur with calibration of instruments or validation of simulations. In this paper we provide indicators of precision (estimates of the variability of the assessment quantity in repeated assessments), since trueness is ensured by the use of calibrated instrumentation.

In terms of methods, the TrioTRAIN Uncertainty Framework distinguishes among a-priori and a-posteriori methods for uncertainty assessment. The former include propagation methods, such as the one prescribed by the *Guide for the Representation of Uncertainty in Measurements*[5], and the Monte Carlo method.[6] With these methods, the sources of uncertainty are first identified, screened, assigned a variability (ideally a probability density function, but often simply its standard deviation or some other representative value). Second, the assigned levels of variability are propagated through a model (of the measurement, of the simulation, of the assessment, according to need), so as to obtain a probability density function (or, more often, a statistical parameter describing it, such as a standard deviation) corresponding to the variability of the quantity being measured, simulated and assessed. This variability represents the uncertainty. On the other hand, a-posteriori methods do not require prior information on the levels of variability associated with many sources of uncertainty. Referring to measurements, as an example, they consist in comparing the results of the intended assessment tool (i.e. measurement instrument) with those of a reference tool. Ideally, the reference tool will have a precision of an order of magnitude better than that of the intended assessment tool. When this occurs, the assessment is called a calibration[7], and the difference between the results of the two instruments under specified conditions is taken as an indicator of the uncertainty.

The objects of the uncertainty analysis are the specific assessment quantity, for which uncertainty is to be determined, and the related variables and processes that allow the analysis to be performed. In the case of this paper, the analysis addresses the uncertainties associated with the TSI assessment quantity for open-air pressure pulse - $\Delta p_{2\sigma}$, the upper bound of a 2σ interval of $(p_{max} - p_{min})$ based on at least 10 independent and comparable test samples (largest value from the seven heights used in the measurements) with ambient wind speeds of less than or equal to 2 m/s. The other objects of analysis are the variables and process of the existing experimental assessment foreseen by the rolling stock TSIs. This analysis also considers the uncertainty of the measurement system required by existing provisions (considered particularly through the existing accuracy requirements of the TSI).

The basis of the analysis consists of the following results obtained in AeroTRAIN, a European project concerned specifically with train aerodynamics (see ~~Grappin~~ Grappein and Rueter[8] for details):

- results of the experimental campaigns;
- parameter variation studies performed on the basis of simulations and experimental results.

Measurements are available for the rolling stock types shown in Figure 2. Except for the German BR440 type, all are in service in Spain. The names of the types are the class names attributed by the respective rail administrations.

An important part of the objects of an uncertainty analysis are the associated variables – e.g. physical

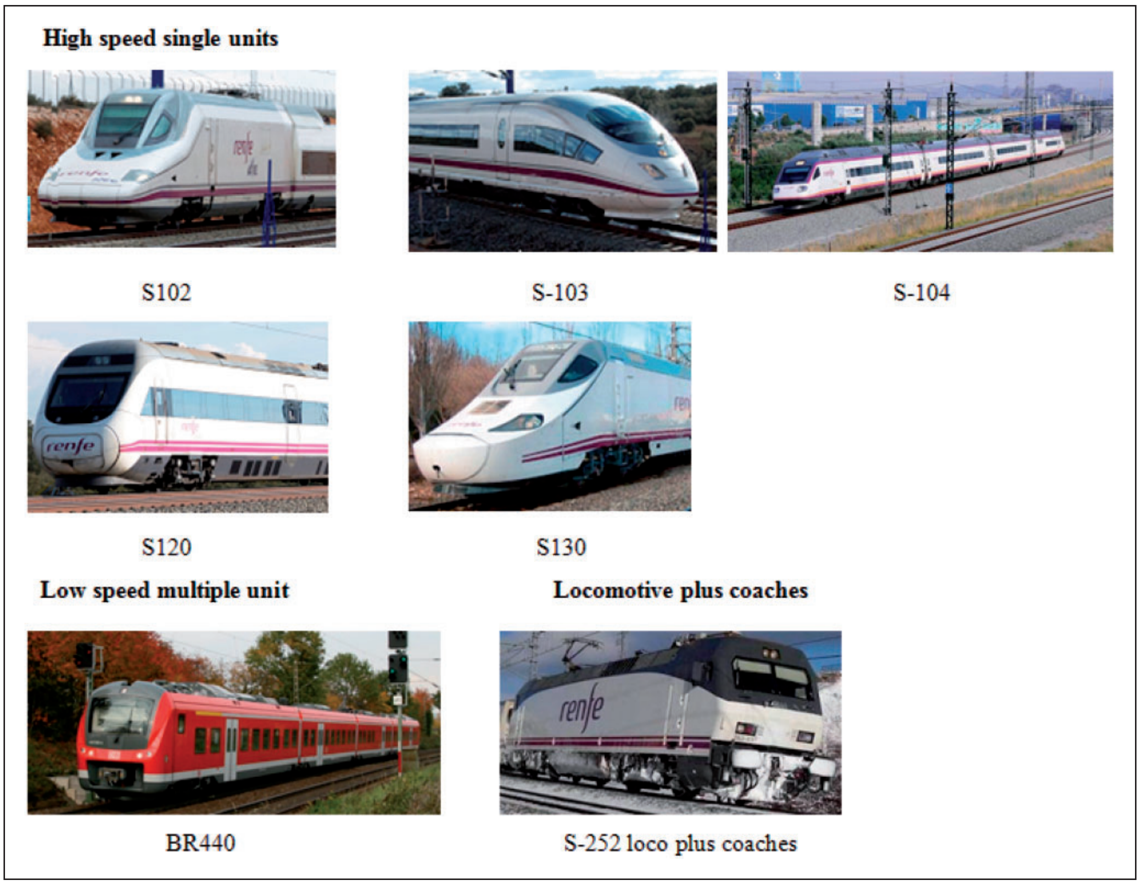

Figure 2. Types of rolling stock considered in this paper.

quantities, instrument settings, variables defined in standards. Such variables may be classified as inter-assessment variables – i.e. variables that are fixed during a single assessment but can vary from assessment to assessment - and intra-assessment variables, i.e. those whose variability occurs during a single assessment. This distinction is purely conventional, since it depends on how the reference document (e.g. TSI) describing the assessment is structured. In an assessment based on site testing, such as the one referred to in this paper, variables describing site characteristics (ballast geometry, position of objects close to the track, etc.) are inter-assessment variables. Train speed, instrumentation noise, ambient wind are examples of intra-assessment variables. Typically, intra-assessment variability contributes to the value of the assessment quantity, as is the case for open-air pressure pulse – it contributes to the standard deviation s in equation (1). On the other hand, inter-assessment variability could affect the value of the mean m if an assessment of the same rolling stock type were repeated, for example, at a different site or with a different measurement setup.

The TrioTRAIN Uncertainty Framework is completed by bibliographic references, such as to standards, TSIs and other documents supporting the uncertainty analysis.

In this paper we combine the most suited a-priori and a-posteriori methods and apply them to the objects described above in order to arrive at representative quantitative indicators of the assessment uncertainty of the open-air pressure pulse.

In the next section 'Influence variables and a-priori analysis', we use the a-priori approach to quantify the relative variability of the measured pressure changes in repeated assessments. Results of parameter studies performed by means of computer simulations and an analysis of the numerous experimental results are used to attribute the levels of variability $v(x_i)$ to the identified influence variables x_i, $i = 1,\ldots,n$. Each influence variable is taken to assume a rectangular distribution, and the variability $v(x_i)$ is represented by the standard deviation of the distribution. A propagation exercise (a-priori method) is performed, leading to estimates of the levels of variability of the measured pressure changes. We assume uncorrelated inputs and linear input/output relationships within the studied range. These assumptions allow the adoption of the well-known 'sum of squares' equation (see ENV 13005[5]) to estimate the variability of a quantity $y = f(x_1, \ldots, x_n)$ depending on n the influence variables $(x_1 \ldots, x_n)$

$$v^2(y) = \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i}\right)^2 v^2(x_i) \qquad (2)$$

The variability $v(y)$ depends on the variability levels $v(x_i)$ of the single influence quantities and the sensitivities $\partial f/\partial x_i$ of y to each of them. A full analysis would require knowledge of the actual distributions. However, this in turn would require significant efforts for most influence variables and was found to be impractical. Therefore, this simplified but cautious approach is used. It is simplified since the necessary parameters are only the extreme values of the distribution. It is cautious in the sense that the flat rectangular distribution has a relatively large standard deviation, given the extreme values, compared with 'peak' distributions i.e. with higher kurtosis, and this eventually leads to overestimates of the variability with all other influences kept constant.

In the '~~A~~-posteriori analyses of the experimental data' section, using the a-posteriori approach, we examine the distributions of the measured pressure changes and of the assessment value. In the 'Summary and conclusions' section, we bring together the results, check them for consistency and draw conclusions regarding the accuracy of experimental assessments of open-air pressure loads.

Influence variables and a-priori analysis

In this section, we use the a-priori approach to analyse the variability of repeated assessments. With such an approach, we look at the effects of each single influence quantity and quantify their relative importance and their contribution to the overall variability. The influence variables were listed, screened, categorized and represented in a 'fishbone' diagram (Figure 3). This type of diagram is used in uncertainty analysis to represent the causal relationships between sources of uncertainty and uncertainty of a measurand or, in our case, of the assessment quantity.

Reading Figure 3 from left to right, the following influence variables are shown.

1. Physical influence variables (PH). These are variables that contribute to determining the pressure field, and the actual pressure change in the measurement positions, around a passing train.
2. Influence variables related to the measurement chain (AT - assessment tool related). These are variables related both to the metrological characteristics of the instrumentation used and to how the instrumentation is set-up. After inclusion of measurement chain contributions we have the quantity Δp_c (the measured and corrected value, the correction being for train speed and air density as required by the reference documents[1–3]). The uncertainty associated with Δp_c is the classic measurement uncertainty.

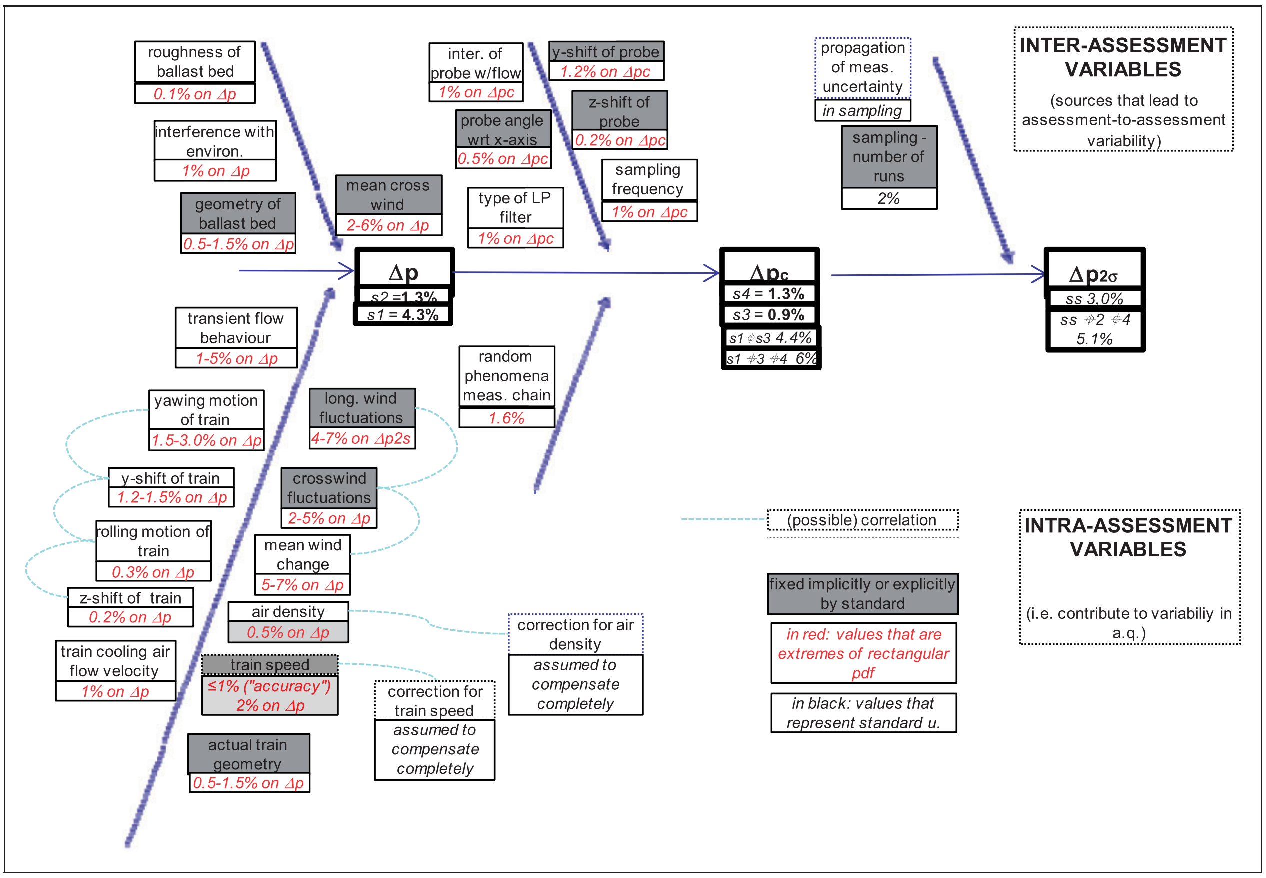

Figure 3. Fishbone diagram of the influence variables for high-speed rolling stock. The diagram refers to one single measurement position (one probe in Figure 1), with the assumption that the uncertainty for all positions are similar.

3. Influence variables related to the processing (PR) required for the determination of the assessment value $\Delta p_{2\sigma}$. These are essentially linked to the required sampling (10 runs are required) and to the propagation of uncertainties through the calculation process described in the Introduction. Both contributions are calculated together here. This last contribution is the one that distinguishes assessment uncertainty from measurement uncertainty. It is evident that these two concepts are different and that assessment uncertainty depends in a fundamental way on what is prescribed by the reference documents.

Reading Figure 3 from top to bottom, one can observe the following.

1. Inter-assessment influence variables.
   These remain fixed (constant) within a single test (i.e. not variable from run to run). They relate to the concept of systematic contributions to assessment uncertainty, since their effect is present during the assessment process as a fixed unknown contribution to the assessment quantity. The relevant PH variables of this type are: geometry and roughness of the ballast bed at the test site; the interference of the setup for the probes (e.g. overhead-contact-line masts) on the surrounding environment and consequently on the pressure field; and the mean value of the crosswind across the 10 runs used for the assessment. The relevant AT-related variables of this type are: positioning errors of the probes (vertical, lateral, angle); type of low-pass filter and sampling frequency used; interference of the probes with the surrounding flow. The relevant PR-related variables are sampling and uncertainty propagation as previously mentioned.
2. Intra-assessment influence variables.
   These are variable within a single test (i.e. variable from run to run or even during a run) and relate to the concept of random sources of variability. Train speed and air density vary from run to run. They significantly contribute to the actual peak-to-peak pressure change, but are assumed not to significantly contribute to the measured value since there is a specific correction for their effects during the measurement. Train motion variables (e.g. lateral shift, roll angle) and other train characteristics can vary from run to run: actual geometry (within construction tolerances), train cooling airflows (on/off, direction). Environmental conditions may vary: mean wind speed (from run to run) and wind fluctuations during a run (e.g. different wind speed between zeroing of the measurement chain and during actual train passage). AT-related intra-assessment variables are essentially noise and signal drifts in the instrumentation. There are clearly no-significant PR-related intra-assessment variables.

The figures in each box associated with an influence value are estimates of the sensitivity of the peak-to-peak pressure change Δp to a variation of the corresponding influence variable. They were systematically determined by means of parameter studies (analysis with computational fluid dynamics, panel methods, measurements, subsequent expert group discussions and verifications), screened and brought together in a list.

The imposed variation of the influence variable in the parameter studies is taken so as to represent limits within which the value of the influence variable itself is very likely (as judged, in our case, by the open-air pressure pulse expert working-party of the AeroTRAIN project) to be contained (its maximum reasonable variation (MRV)). (This adjective is a link to the subjective approach to probability and uncertainty,[5] in which the judgement of the analyst is considered as an inevitable and valuable contribution to the analysis.) As an example, train speed, air density and ambient wind all have specified ranges of values within which the test run is considered valid. Therefore, it is unreasonable to assume that values outside this range are included in an assessment process; hence, the MRV is defined by this range. Another example consists of quantities related to train movement: if 10 trains of a certain type pass the same wayside measurement site, there will be slight variations of the relative position of the car-body with respect to the probes due to different car-body oscillations or car-body assembly. Whereas it is difficult to exactly quantify these influences, it was relatively easy to estimate values that it would be unreasonable to exceed (e.g. assembly tolerances, maximum displacements that may be encountered on straight track determined on the basis of measured signals). Hence, a MRV may be quantified for these variables. Still another example of quantification is discussed below in relation to the effect of crosswinds during measurements.

The concept of a MRV is quite important for cases, such as the one illustrated in this paper, in which analytical and numerical computations require significant effort, de facto impairing a comprehensive analysis that takes into account correlations and nonlinearities and the full (joint) probability density functions of the influence variables.

With such a simplified, but comprehensive approach, rectangular probability density functions may be taken for the subsequent uncertainty analysis, with limits corresponding to the MRV. However, it was not these maximum values that were propagated, rather the corresponding standard values (the standard deviation of a rectangular distribution is obtained simply by dividing the limit value by $\sqrt{3}$). This is to take into account that it is unlikely that all influence variables assume, by chance, values that are simultaneously close to the limits.

The results of the propagation calculation are shown respectively in Tables 1 and 2 for the PH

Table 1. Influence of PH variables on HS rolling stock.

	MRV a (%)	Standard uncertainty (%) of rectangular distribution $s = a/\sqrt{3}$	Without negligible contributions (%)	Without wind contribution (%)
Intra-assessment variables				
Train speed	2.0	~~0.00~~		0.00
Air density	0.5	~~0.00~~		0.00
Overall wind	7.0	4.04	~~0.16~~	
Yaw movement	1.5	0.87	~~0.01~~	0.87
Lateral movement	1.2	0.69	~~0.00~~	0.69
Roll movement	0.3	0.17		0.17
Vertical movement	0.2	0.12		0.12
Transient flow behaviour	1.0	0.58		0.58
Train cooling airflows	1.0	0.58		0.58
Expected variability s_1	7.4	4.3	4.2	1.4
Inter-assessment variables				
Interference with environment	1.0	0.58		0.58
Ballast geometry	0.5	0.29		0.29
Ballast roughness	0.1	0.06		0.06
Mean crosswind	2.0	1.15	1.15	
Expected variability s_2	2.3	1.3	1.2	0.6

Table 2. Influence of PH variables on CR rolling stock.

	MRV a (%)	Standard uncertainty (%) of rectangular distribution $s = a/\sqrt{3}$	Without negligible contributions (%)	Without wind contribution (%)
Intra-assessment variables				
Train speed	2.0	~~0.00~~	0.00	0.00
Air density	0.5	~~0.00~~		0.00
Overall wind	11.0	6.35	6.35	
Yaw movement	3.0	1.73	1.73	1.73
Lateral movement	1.5	0.87		0.87
Roll movement	0.3	0.17		0.17
Vertical movement	0.2	0.12		0.12
Expected variability s_1	11.5	6.6	6.6	1.9
Inter-assessment variables				
Interference with environment	1.0	0.58		0.58
Ballast geometry	1.5	0.87		0.87
Ballast roughness	0.1	0.06		0.06
Mean crosswind	6.0	3.46	3.46	
Expected variability s_2 (%)	6.3	3.6	3.5	1.0

influence variables (left-hand part of the fishbone diagram, variability factors s_1 and s_2, see below for discussion), and in Table 3 for the AT-related influence variables (central part of the fishbone diagram, variability factors s_3 and s_4). Summary values are also shown in the fishbone diagram, considering moreover the results discussed in the next section.

The following assumptions apply for this calculation.

1. Subtraction in order to obtain the peak-to-peak difference. The effect of uncertainty propagation in the operation of forming the peak-to-peak difference Δp from the pressure signal is not separately considered; rather it is included in the measurement uncertainty. This simplifies the analysis since all variability factors, sensitivities and uncertainties can be referred to the pressure differences Δp rather than to the pressure values.

Table 3. Influence of AT variables on HS and CR rolling stock.

	MRV a (%)	Standard uncertainty (%) of rectangular distribution $s = a/\sqrt{3}$	Without negligible contributions (%)
Intra-assessment variables			
Random, measurement chain	1.6	0.92	0.92
Expected variability s_3		0.9	0.9
Inter-assessment variables			
y-shift of probe	1.2	0.69	0.69
z-shift of probe	0.2	0.12	
Angle of probe	0.5	0.29	
1 Type of LP filter	1.0	0.58	0.58
Sampling frequency	1.0	0.58	0.58
Interference of probe with flow field	1.0	0.58	0.58
Expected variability s_4	2.2	1.3	1.2

2. Correlations are possible between the variables connected with vehicle suspension movements and with ambient wind (see Figure 3, dashed lines). Nonlinear relationships between output and influence variables are also present within the range assumed by the influence variables. Both of these aspects would not justify the use of propagation by 'sum of squares', which rigorously applies to linear models with uncorrelated inputs. Nevertheless, the calculation is performed this way and we will see in the following sections that the results of the a-posteriori approach are consistent. This is taken to mean that the propagation calculation is representative of the actual physical phenomenon, also in terms of influence of each quantity. This might also be expected – in fact if there were significant nonlinearities and correlations within the explored range, it would probably be difficult to obtain repeatable experiments (e.g. a small change in one variable would cause surprisingly large changes in results). The evidence available suggests that this is not the case, although it cannot be completely.

In Tables 1 and 2 the contributions of the PH influence variables of the pressure change Δp caused by passing trains are appraised, distinguishing between high-speed (HS) rolling stock (streamlined 'closed' shapes) and conventional rail (CR) rolling stock ('blunt' shapes).

The following factors are shown in these tables.

1. The influence variables that were retained after initial screening, distinguished between inter- and intra-assessment categories.
2. The MRVs - in relative, or percentage, terms - of the measured peak-to-peak pressure change Δp when the corresponding influence variable assumes its MRV.
3. The corresponding standard values.
4. The expected relative standard intra-assessment variability s_1 (quantification of variability v_1) obtained with equation (2); this estimated variability is a fixed site, experimental variability which, when combined with the corresponding intra-assessment AT-related variability, gives the measured experimental variability of Δp_c represented by s in equation (1).
5. The expected relative standard inter-assessment variability s_2, obtained with equation (2); this estimated variability corresponds to the variability of the pressure change Δp that we would encounter if we repeated the assessment process on the same rolling stock type allowing the test site to vary within a range of standard and compliant conditions.
6. Similar variability functions obtained by eliminating influence variables that proved to be negligible, or sources that proved to be dominating (ambient wind), in order to highlight them more effectively.

The following main conclusions were drawn from the obtained results.

1. Wind appears to be by far the largest source of both intra-assessment variability s_1 and inter-assessment variability s_2, for both types of rolling stock. Physical intra-assessment variability arises mainly due to wind fluctuations in the x- (longitudinal) and y- (transversal) directions and differences in the wind speed between the time of its measurement and the time of the train passage. This contributes to the standard deviation s for 10 runs $s = \sqrt{s_1^2 + s_3^2}$. A MRV of the peak-to-peak pressure due to this cause was assumed to be 7% for HS rolling stock and 11% for CR rolling stock. The ambient wind speeds tends to be dominant for both types – when removed, the predicted intra-assessment variability decreases from

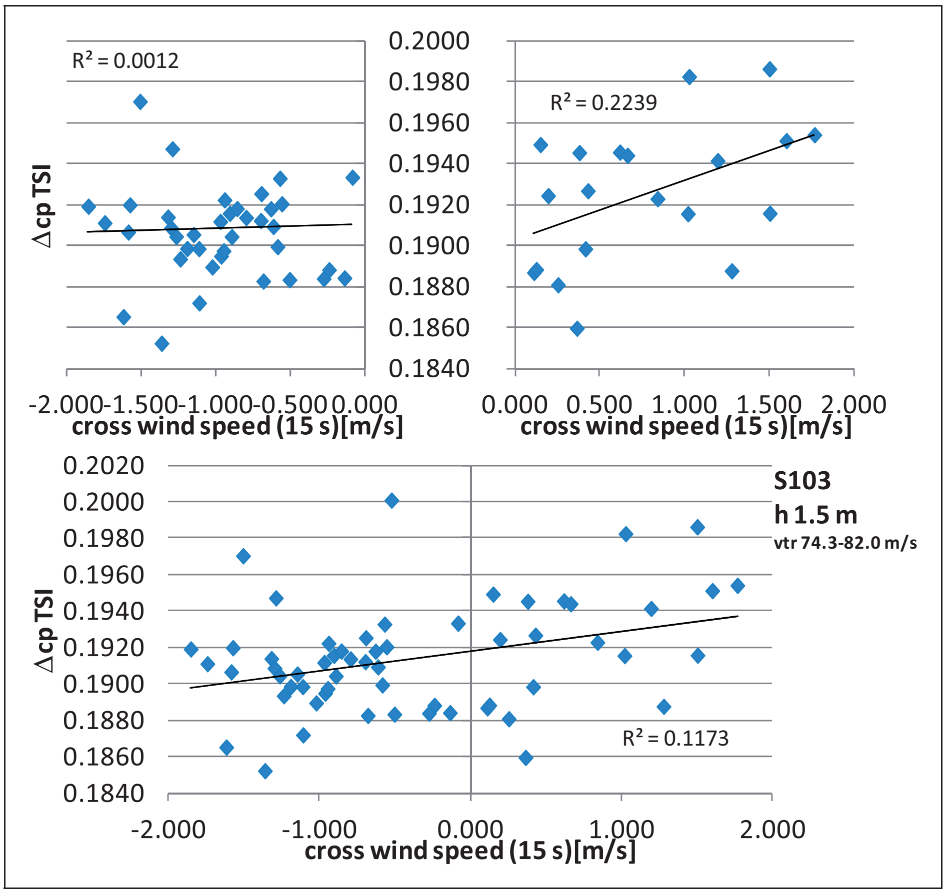

Figure 4. The S103 type rolling stock. Normalized TSI peak-to-peak pressure changes plotted against crosswind speed measured in the 15 s prior to train passage. The data on the top and bottom parts of the figure are the same. The difference is that in the top part the regressions refer separately to a negative crosswind speed (wind from track towards probes) and positive crosswind speeds (from probes towards the track).

4.3% to 1.4% (HS) and from 6.6% to 1.9% (CR). Similarly, its contribution to the physical inter-assessment variability decreases from 1.3% to 0.6% (HS) and 3.6% to 1.0% (CR).

2. As outlined above, we assumed that the variations of the value of Δp due to train speed and air density are correlated, with a correlation coefficient value of one, with the corresponding corrections. This leads to a net effect on Δp_c (corrected value) that is zero. In terms of the contribution to the actual pressure change, whereas train speed appears to have a non-negligible effect on Δp, the air density appears to have a small effect, which leads to question: Is a correction needed?

In order to more clearly illustrate the effect of the mean crosswind on the TSI assessment (i.e. the physical inter-assessment variability due to the fact that the wind may change between tests), two plots are shown (Figures 4 and 5) for the S103 type rolling stock. This type is not the one for which the effect is the largest (which is the BR440 type). However, it is the type for which the largest number of runs is available, facilitating the analysis. Figure 4 shows the TSI normalized pressure change values (Δc_p) for each

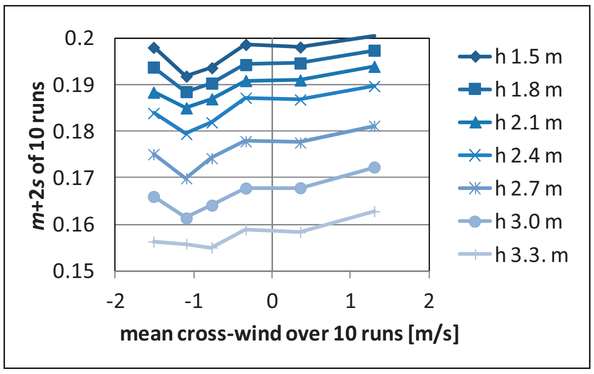

Figure 5. The S103 type rolling stock. Assessment values $m+2s$ calculated for the data of Figure 4 ($h = 1.5$ m) and also for different probe heights, plotted against crosswind speed measured in the 15 s prior to train passage.

available run with a (total) wind speed of less than 2 m/s, plotted against the crosswind speed. Figure 5 shows the same runs as above but processed differently: the runs are sorted by increasing crosswind speed; then the normalized pressure change values are grouped 10 by 10; finally the TSI assessment value $m+2s$ is calculated and plotted against the mean crosswind speed for each group.

From Figure 4, we can conclude that an effect due to the mean crosswind variability is visible for positive wind speeds (i.e. from the train towards the probes). A MRV of about 2% (from the figure, $= 0.004/0.191$, where 0.004 is the variation read on the y-axis due to wind speed over the entire range of interest and 0.191 the mean value) is taken to represent the difference that could occur when measuring with wind speeds approaching $+2$ m/s with respect to a situation with no wind (this is the value that appears in Table 1). A value of 6% is taken to be representative for CR trains, using similar reasoning.

This example further clarifies how MRVs may be estimated.

The uncertainty sources connected with the measurement chain are quantified in Table 3. The MRV due to random uncertainties in the measurement chain, based on the metrological characteristics of the instrumentation used for the AeroTRAIN experimental campaigns, is consistent with the 2% accuracy requirement of the current regulatory framework. The MRV for inter-assessment variables were quantified by means of appropriate modelling and/or data analysis as outlined above. Both contributions s_3 and s_4 proved to be of the order of 1% (standard value).

The 2% accuracy level prescribed in the reference documents, intended as a maximum admissible error, proves to be quite consistent with the uncertainties behind the assessment. In fact, for the lowest value of s_1 measured (S103 type, 1.6%), the instrumentation just meeting the accuracy requirement would alter the overall intra-assessment variability $\sqrt{s_1^2 + s_3^2}$ by about 20% (cautiously assuming that the errors in the measurements are uniformly distributed).

Having analysed the contributions of the different influence variables, using both experimental data and theoretical calculations (including simulations), we now examine, in a different way, the experimental data and its variability.

A-posteriori analyses of the experimental data

The purpose of these analyses was to provide indicators related to assessment uncertainty by looking at the variability within the experimental data and checking for consistency with the results of the a-priori analysis.

The analysis of this variability was mainly focused on the S103 data, for which the largest number of runs was available. The other rolling stock types were checked to make sure the conclusions were not significantly different.

First of all, the measured values were checked for normality. The normal probability plot (in this type of plot, the data are perfectly aligned if they are normally distributed) in Figure 6 shows the measured normalized pressure change values at the seven different 'TSI heights' (at 2.5 m from the centre of the track). The distributions are characterized by the mean values that can be read on the x-axis of the normal probability plot (along the line '0') and by the relative standard variability of about 1.6% of the mean values (e.g. for the sensor height of 1.5 m, a variability of about (0.194–0.188)/2 with a mean of 0.191: compare also with Figure 4). Normality tests using the Anderson–Darling and Lilliefors approaches (see, for example, Dietrich[7]) confirmed the impression obtained from visual inspection that the data cannot in general be assumed to be normally distributed. Some data do approach normality (e.g. at the height of 1.5 m).

A possible explanation for this behaviour is connected with the observations regarding the effect of wind (see Figures 4 and 5). In the S103 tests, the

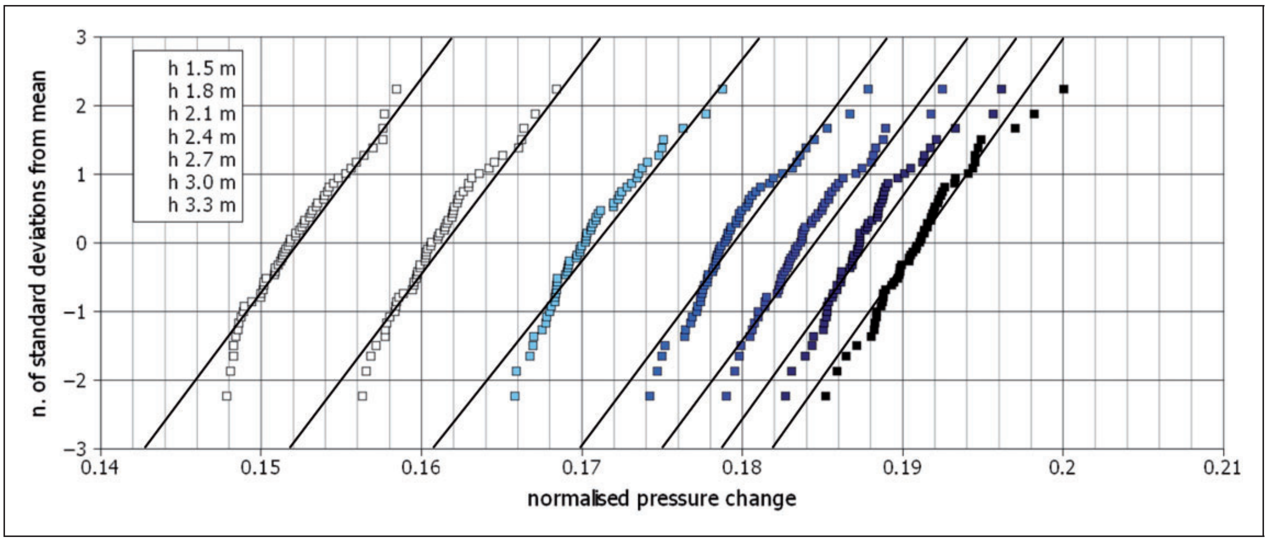

Figure 6. Normal plot of S103 rolling stock data (56 TSI compliant runs), black marks the lowest ~~height of a probe~~.

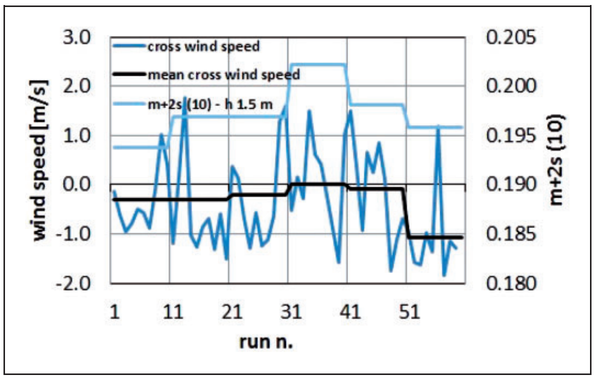

Figure 7. Data obtained on the S103 rolling stock (56 TSI compliant runs, in order of measurement). Assessment value ($m + 2s$ of 10 runs) plotted against crosswind speed (and its mean).

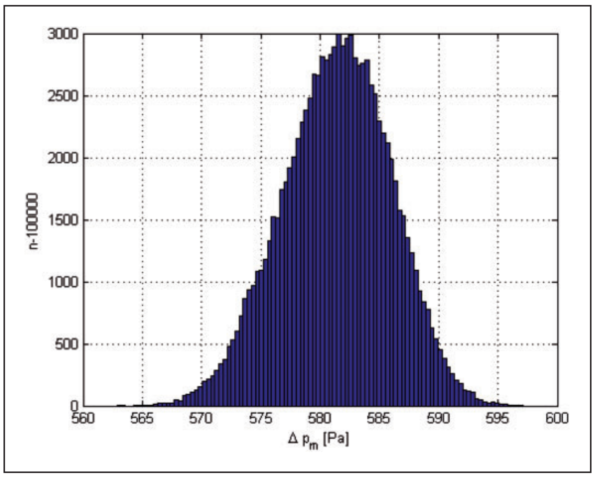

Figure 8. Histogram of 100,000 values of $m + 2\,s$ at $z = 1.5$ m derived by randomly drawing 10 of the 59 S103 measurements that conform to the TSI.

wind did not randomly vary around a zero mean, rather it generally had a negative sign (see Figure 7). Given its significant effect on the results, it could be a possible cause for non-normal distributions.

The assumption of a normal distribution leads to simplifications in the calculation process for the variability of the assessment quantity $\Delta p_{2\sigma}$, which can be performed analytically. This type of calculation is described here and is used in conjunction with a bootstrap calculation,[9] which does not require the data to be normally distributed. (A subsample of a size less than or equal to the size of the data set was generated from the data, and the statistic $m + 2s$ was calculated. This subsample was generated with replacements so that any data point could be sampled multiple times or not sampled at all. This process was repeated for many subsamples. The computed values for the statistic form an estimate of the sampling distribution of the statistic.)

The analytical calculation is now briefly described. The assessment quantity based on TSI was obtained using equation (1). This calculation was usually performed within one single assessment for authorization. The AeroTRAIN data allows the possibility to calculate how this quantity would vary if several different assessments were performed on the same type of rolling stock. This variability, if combined with the variability that would arise if experiments had been possible on numerous different sites, provides an indication of the uncertainty associated with the single assessment for authorization.

Given the assumption of a normal parent distribution, the mean m can be shown to be distributed as a Student's t distribution and the standard deviation s as χ^2.[7] These two distributions are statistically independent, thus it is possible to determine the variability of $m + 2s$ by a 'sum of squares' approach.

The uncertainty on the mean approximately follows the well-known formula

$$u(m) = s/\sqrt{n} \tag{3}$$

which is valid for a known standard deviation σ of the parent distribution and represents, in turn, the standard deviation of the normal distribution that can be taken to approximate the t-distribution of the mean (this is associated with a confidence probability of 68%, coverage $k = 1$). This is not exactly our case: we have an estimate s_ν of the parent standard deviation, with $\nu = n - 1 = 10 - 1 =$ nine degrees of freedom. In the latter case the variability should be multiplied by a factor slightly greater than one.[7] This approximation was deemed acceptable for the purposes of this calculation.

Regarding the uncertainty of the standard deviation, s_ν, of the sample, an approximate formula is also available[5]

$$u(s) = [2(n-1)]^{-0.5} \tag{4}$$

This formula is also based on a normal approximation of the actual χ^2 distribution. The degree of approximation of this approach has been analytically verified for the similar issue of slipstream airspeed measurements (see Baker et al.[10,11]), and we cross-checked the results against the results of the bootstrap calculation (Figure 8). It can be seen how the distribution of Figure 8 is, in fact, slightly skewed and is not exactly normal. As previously mentioned, this is a result of the convolution of the t-distribution for m and the χ^2-distribution for s. The mean value of this distribution is approximately 580 Pa and its standard deviation is approximately $11/2 = 5.5$ Pa (relative value $5.5/580 \approx 1\%$). The corresponding analytical calculations yielded a relative variability of $m + 2s$ of 0.88%.

Therefore, the approximate calculation is used for the considerations that follow. However, a slight underestimation is expected for this reason.

Figure 9 shows the results of the analytical calculation as a function of the ratio of the standard

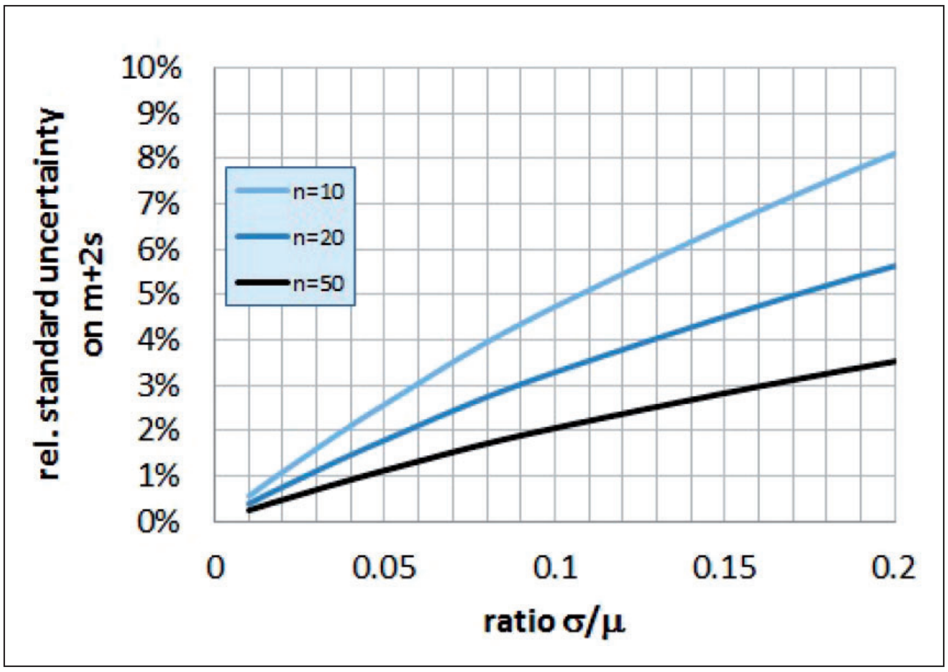

Figure 9. The relative standard variability on the assessment quantity $m+2s$ obtained from an analytical calculation assuming a normal parent distribution with standard deviation σ and mean μ.

deviation to the mean (σ/μ) of the parent distribution. Note that for our case $s=\sqrt{s_1^2+s_3^2}$ is a good estimate of this parameter, if relative values are used. Substituting s onto the x-axis of the chart allows us to read the corresponding variability of $m+2s$ (assessment uncertainty at a fixed site) on the y-axis.

For the vehicle types analysed in AeroTRAIN, the ratio, estimated on the available samples, varies between 0.016 (for the S103 examined above) and 0.090. Considering that the number of runs per sample considered (the TSI value) is 10, the expected relative standard variability of the assessment quantity $m+2s$ measured on the same type of vehicle at the same site ranges from just under 1% (again, the case examined in detail above) to just over 4%.

Summary and conclusions

Table 4 summarizes the values derived in the previous tables and combines them in order to arrive at figures for indicators of the overall assessment uncertainty.

The a-priori figures from the propagation exercise are compared with a-posteriori figures for trains that have a significant number of runs available (essentially type S103 - with 59 valid runs - and S104 - 16 runs - for HS and BR440 - 47 runs - for CR).

The expected experimental variability of the Δp_c measured at a fixed site is, for HS rolling stock, $\sqrt{s_1^2+s_3^2}=4.4\%$, compared to which the contribution of the measurement chain s_3 correctly proves to be negligible, turns out to be compatible with the observed experimental variability (for S103 and S104 HS rolling stock), which ranges between 1.6 and 4.4%. The same can be said for CR, in which the propagated variability amounts to 6.7%, as compared with 9% of the BR440.

The above values for experimental variability provide us with an estimate of the ratio σ/μ that can be used, in conjunction with the analytical method of the a-posteriori analyses (see Figure 9), to estimate the variability s_s of the assessment quantity $\Delta p_{2\sigma}$. For a relative standard variability of 4.4% (HS) we obtain an estimate for the standard variability of $\Delta p_{2\sigma}$ of $s_s=2.3\%$. For CR rolling stock we obtain $s_s=3.4\%$.

However, TSI assessments may be performed at a wide variety of different sites, all compliant with the requirements, and this logically increases the uncertainty due to the inter-assessment sources of variability. An indication of this uncertainty, which is our final goal in this paper – i.e. a figure for TSI assessment uncertainty – is obtained by 'adding' to s_s the contributions of the sources of inter-assessment variability $\sqrt{s_2^2+s_4^2}$ (mainly wind, differences in track geometry, measurement system biases - see inter-assessment contributions in Tables 1 to 3).

We conclude that an indication of the TSI assessment uncertainty is of the order of $\pm 3\%$ (standard value) for HS and $\pm 5\%$ for CR, and could be up to $\pm 8\%$ depending mainly on the run-to-run variability associated with the type of train and on the characteristics of the ambient wind at the moment of the tests (in particular on wind direction). The corresponding 95% confidence limits can be taken as double these values (respectively $\pm 6\%$ HS and $\pm 10\%$ CR), if we also assume that the assessment

Table 4. A summary of the levels of variability and the estimates of the overall assessment uncertainty ($\pm$ indicates that the combination was achieved using the 'sum of squares' approach).

		From propagation (%)	Experimental (%)	Comments
HS				
s_1	PH - intra-assessment variability of pressure change Δp	4.3		
s_2	PH - inter-assessment variability of pressure change Δp	1.3		
s_3	AT- intra-assessment variability of pressure change Δp	0.9		
s_4	AT- inter-assessment variability of pressure change Δp	1.3		
$s_1 \pm s_3$	experimental intra-assessment variability of Δp (=measurement uncertainty, fixed-site)	4.4	1.6–4.4	S103, S104
Sampling and propagation (effects of processing)				
s_s	Variability of $\Delta p_{2\sigma} = m + 2s$ of 10 runs, fixed-site	2.3	1.8	S103
Assessment uncertainty including inter-assessment components				
$s_s \pm s_2 \pm s_4$	Estimated assessment uncertainty (on $\Delta p_{2\sigma}$, including site-to-site bias)	3.0		
CR				
s_1	PH - intra-assessment variability of pressure change Δp	6.6		
s_2	PH - inter-assessment variability of pressure change Δp	3.6		
s_3	AT- intra-assessment variability of pressure change Δp	0.9		
s_4	AT- inter-assessment variability of pressure change Δp	1.3		
$s_1 \pm s_3$	Experimental intra-assessment variability of Δp (=measurement uncertainty, fixed site)	6.7	9.0	BR440
Sampling and propagation (effects of processing)				
s_s	Variability of $\Delta p_{2\sigma} = m + 2s$ of 10 runs, fixed site	3.4	3.8	BR440
Assessment uncertainty including inter-assessment components				
$s_s \pm s_2 \pm s_4$	Estimated assessment uncertainty (on $\Delta p_{2\sigma}$, including site-to-site bias)	5.1		

quantity is normally distributed; an assumption that gives a reasonable approximation for our purposes.

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