SP ENERGY NETWORKS

Flexible Networks for a Low Carbon Future

Technical Note On Data

- Error Detection and Correction

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1. Introduction

In the measurement of power system quantities and other phenomena (e.g. weather) as part of a Flexible Network or Smart grid approach (or indeed for more traditional planning and operational purposes), it is inevitable that failures and errors in measurements will occur. This report describes experiences of the detection and correction of such errors as part of the Tier 2 Low Carbon Networks Fund project “Flexible Networks for a Low-Carbon Future”.

2. Data Error Detection

It should be recognised that all measurements are generally subject to error to some degree. In a well-designed measurement process, these “routine errors” will usually be small, and well-understood. They may include quantisation errors, in which the measured value must be fitted to a fixed precision representation (which may be thought of as equivalent to a fixed number of decimal places). Calibration uncertainty will arise in relation to the measurement devices themselves. Derived measurements which are based on a number of actual measurements of a raw quantity (for example RMS voltages, which are based on a sufficient number of spot voltage measurements to characterise the waveform) are subject to an averaging effect which to a degree smooths out rapid changes in the measurement. Within the bounds of these errors and uncertainties, the measurement will still characterise well the underlying physical phenomenon being observed.

However, from time to time, larger errors will be encountered, such that the measured value is not representative of the observed quantity. In some cases, no value will be recorded. These errors may result from a failure of the measurement device, its interface to the system being monitored or the communications channel by which the measurement is transported and stored. ‘Spurious’ measurements may in fact be correct in terms of the physical phenomena observed, but may indicate that the power system (or other observed entity) has moved into a state which is not of interest from the perspective of the user of the measurements. An example might be a change in distribution system configuration which temporarily transfers additional load onto a substation. The augmented substation load is not of interest to a planner in determining the annual peak load of the substation, but the fact of this transfer may only be detectable through the change in the measured load, following which measurements under the abnormal configuration can be excluded from determination of the peak.

Large errors can often be detected by applying a simple thresholding technique, where the threshold is set to a level such that measurements above or below this value are physically implausible, or at least highly suspect. Examples might be a current measurement threshold at a low integer multiple of the rating of the item of plant being measured, or a voltage measurement thresholds at 50% and 150% of nominal. Under almost all circumstances, the physical conditions corresponding to such measurements could not occur, and thus the measurements should be regarded as erroneous. This approach has been found to be useful as an initial filtering step in the detection of errors in data to be used for practical analysis, but further steps are also necessary.

Smaller errors cannot reliably be detected by such simple approaches. In such cases, measured values are physically plausible, and in seasonally varying quantities, might be regarded as 'true' measurements at other times of year or in other circumstances. They are, however, distinct from other 'true' measurements around the time of measurement. For these approaches, a statistical approach which quantifies the 'unexpectedness' of a measured value has been found to be effective.

Many measurands of interest in the planning and operation of power systems follow regular daily, weekly and annual patterns. For such measurements, a method based on a short-term forecasting method published in the academic literature[1] has been applied. This method uses a *detrending* approach using annual and weekly measurement profiles (which are averaged over the preceding several years and weeks respectively) to produce a series of 'expected' measurements which are reflective of actual previous behaviour of the measurand over that time period. Inevitably, the actual measurements will differ from these expected values, but where the underlying process or phenomenon being measured is consistent over the period, it is expected that the scale of the differences will be consistent over time.

The statistical distribution of recent differences between expected and measured values in data which is thought to be correct can provide guidance on the likely range of variation. Assuming a normal distribution of differences with zero mean, 99% of measurements will lie within ±2.57 standard deviations of the expected value, while 95% will lie within ±1.96 standard deviations. This test is implemented by calculating the standard deviation of the recorded differences over a suitably large number of previous measurements (in Flexible Networks, for power measurements at 10-minute intervals, 8 weeks of data was used). For a 99% acceptability band, measurements which differed from the expected value by more than 2.57 standard deviations would be regarded as suspect. This is shown in Figure 1, which also shows the 99.9% acceptability band. Since this band must contain 99.9% of measured points, it is wider than the 99% band.

[1] D.C. Hill and D.G. Infield, "Modelled operation of the Shetland Islands Power System comparing computational and human operators' load forecasts", IEE Proceedings: Generation, Transmission and Distribution, Vol. 142, No. 6, 1995, pp555-559.

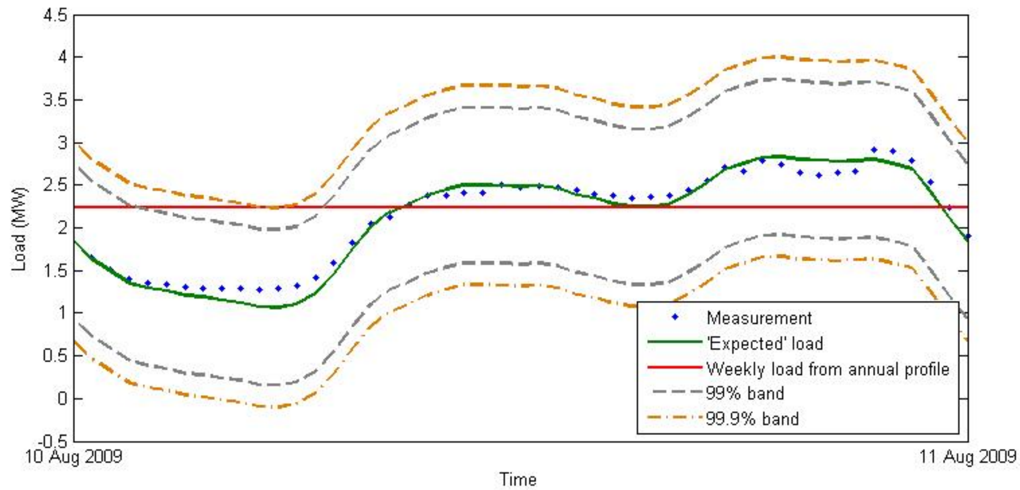

Figure 1: Trend based approach to identifying suspect data points

It is advisable to calculate and identify the statistical distribution of the differences, and then to use a standard table describing the distribution to identify the parameters for the chosen acceptability band. The acceptability band can be thought of as reflecting the ‘false positive’ rate. With a 99% band, 1% of ‘true’ measurements would be expected to be marked as suspect, while for a 95% band, 5% of ‘true’ measurements would be so marked. The 99% band is thus wider than the 95% band.

Over the long term, this method therefore has a clearly defined rate of ‘false positives’ in error detection. The rate of ‘false negatives’ or undetected errors is less well defined, and depends on the error characteristics of the measurement process and the behaviour of the quantity being measured. However, the maximum size of any undetected error is fixed in relation to the variability of the measured quantity, as defined by the statistical distribution of recent differences.

This approach has been found to be effective in quantities which follow a regular pattern, and are not subject to sudden, unexpected disturbances – for example power and current measurements in primary and secondary substations.

Since the definition of an ‘abnormal’ measurement is based on the statistical properties of recent measurements, this method will inherently adapt to sustained changes in the nature of the system being monitored, although at the cost of degraded performance during the adaptation. This is illustrated by considering its application to a voltage measurement data series obtained from the HV busbar of Ruabon primary substation:

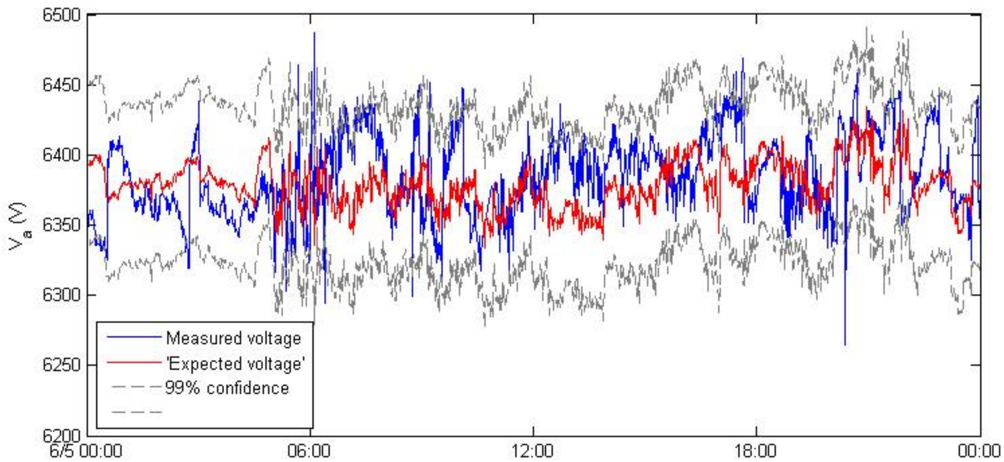

Figure 2: Application of trend-based approach to voltage measurements

In Figure 2, the method has, based on the previous 4 weeks of voltage measurements, established a 99% acceptability band of around ±50V around the 'expected' value. As previously discussed, a few measurements per day fall outside this band. A larger acceptability band (perhaps 99.9%, corresponding to about 65–70V) might identify the one or two obvious outliers on this day.

Figure 3 shows the effect of the application of a 3% voltage reduction as part of the voltage reduction experiment at Ruabon primary substation:

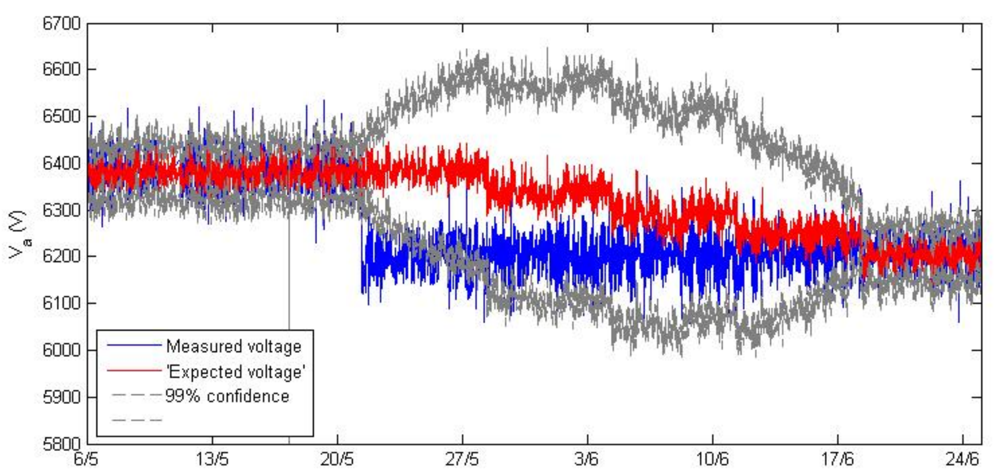

Figure 3: Effect of large sustained change in measured quantity

The 3% voltage reduction results in a change in measurement of about 200V, four times the statistical acceptability band. As a result, all measurements immediately following the change are identified as suspect. However, over the following four weeks (corresponding to the amount of data used to calculate the expected values and acceptability band), the error detection method adapts to the change in three stages:

1. The acceptability band broadens, because the apparent variability of the measurements over the four-week window increases as more measurements at the new lower voltage are made.
2. The series of expected values gradually approaches the new lower voltage level. The weekly recalculation of the expected voltage profile can be discerned
3. The acceptability band reconverges to around ±50V as the variability in the previous 4 weeks measurements returns to its typical long-term value through the replacement of higher-voltage measurements with lower-voltage measurements.

The ability of the detection method to detect suspect data points during this adaptation process is degraded, firstly because the initial measurements following the voltage reduction are mistaken for errors, but more importantly because the statistical acceptability bands widen significantly during the adaptation. Reducing the period over which the acceptability bands and expected value are calculated from 4 weeks will hasten the adaptation process, but will render the method more susceptible to being influenced by a small number of erroneous measurements or temporary changes in system conditions.

Regardless of the method of identifying data errors, it is important that any pattern in their occurrence is identified and investigated. A permanently occurring error indicates, of course, a persistent failure or interference with the measurement system. The nature of the error may provide an indication of the failure which has occurred. Recording and disseminating the knowledge resulting from investigation of such failures can improve response to similar observed errors in the future. For example, it was noted that voltage measurements on one or more LV phases at a secondary substation of would occasionally reduce from a nominal value of 230–250V to around 30V and remain at that level. On investigation, it was found that the fuse in the connection between the LV busbar and the substation monitor had failed. This knowledge enables improved response to such failures in the future.

Intermittent data errors should be examined for any consistent temporal pattern. Such patterns might be detected graphically, by plotting the occurrence of errors over different time periods – for example, the time of day at which errors occur might be plotted. Alternatively, daily or weekly error characteristics could be calculated. Errors which occur at a consistent point in time may be indicative of interference arising from a local source, or resulting from regular interfering activity within the measurement and communication system.

3. Error Correction

Error correction involves the substitution of artificially created “pseudo measurements” for missing or erroneous points in a measurement series. In many cases, error correction can be more easily and consistently undertaken some time after the time of the problematic measurement point, rather than attempting to insert values into a “live” measurement stream. Later correction allows the substitute values to benefit from an understanding of how the measured quantity behaves both before and after the time of the missing data – this can be thought of as interpolation rather than extrapolation.

Consideration should first be given to whether correction of errors in a particular measured quantity is both possible and required. If the analysis for which the measurements are to be used is tolerant of missing data in the quantity and pattern observed, the simplest approach is to discard the missing or suspect data points, and proceed with the analysis using the remaining 'good' data. For example, in the assessment and calibration of a primary transformer temperature model as part of Flexible Networks, two measurements of transformer temperature were not recorded in the middle of the experiment. Since these two points represented less than 1% of the experimental period, did not cover a period of particular interest which was otherwise unrepresented, and were expected to have only a small effect on the comparison between modelled and actual behaviour, they were simply excluded from the analysis. By contrast, a full day of temperature measurements was unavailable at the beginning of the experiment. These measurements would have covered the 'heating up' phase of the transformer's behaviour following a sudden load increase, behaviour of considerable interest which was not otherwise represented. However, since no alternative source of information which would provide information about the transformer's temperature was available, and considering that the purpose of the experiment was to calibrate a model (which could not therefore be used as a source of substitute pseudo measurements), it was considered impossible to correct this error, and the period was excluded from the experiment.

A second example concerns the assessment of an appropriate interval for the routine measurement of network voltages. This involved the assessment of the effect on the annual statistical distribution of measured voltages of alternatives to the 'raw' 1-minute sampling interval for a number of primary and secondary substations. In this case, the extent to which the measurement series covered the time period of the analysis was assessed, as was the effect of erroneous measurements on the reduced sample distribution. It was found that at least 75% of expected measurements were available (with one outlier at 65%) and that altering the sampling rate did not significantly affect the coverage for any individual substation.

In other cases, it will be necessary to reconstruct a suitable value to permit the required analysis. For example, many short-term load forecasting models use auto-regressive and/or moving average processes, in which the forecast value is dependent on observed recent values. Similarly, the IEC 60076-7 transformer thermal model requires a continuous sequence of load and ambient temperature measurements to estimate the current temperature model. In both of these examples, a missing or significantly erroneous measurement will degrade or disrupt the process.

Isolated errors and short sequences of problematic measurements may be substituted by extrapolation from recent values, or when data is analysed after the event, by an average or trend connecting satisfactory measurements made beforehand and afterwards. Where, as in a load forecasting process, the analysis produces an estimate of the measured value, it may be possible to substitute the estimate or forecast for a missing or rejected estimate. The shortest-term available forecast should be used in such a case. It will be appreciated that this process will inevitably lead to the estimate drifting from reality over time, and such an approach should only be used for a short period before other approaches must be used.

Where more than a few consecutive measurements must be corrected, it will be necessary to construct a replacement data series from alternative or historical measurements. In some situations, it may be straightforwardly possible to reconstruct missing or erroneous values from other measurements. An example might be a primary substation in which all incoming transformer connections and outgoing HV feeders are monitored. In the event of error or failure in a current measurement, a corrected value could be reconstructed arithmetically from other measurements made at the same time. Flexible Networks experience suggests that measurement failures will often affect many of the measurements required to make such a substitution, but it may be appropriate in combination with other methods, as discussed further below.

For some measurements, acceptable results may be achieved by directly substituting an alternative source of measurements for the missing or suspect measurements. In such cases, the pattern of 'correct' measurements should be compared with corresponding values from the substitute source to determine its acceptability. For example, in the initial calibration of the IEC transformer thermal model, there were significant gaps in the series of measured ambient temperatures at the primary substation concerned. Nearby primary substation and public weather stations were considered as substitutes, by directly plotting the correct measurements from the primary substation against the alternative (as shown in Figure 4), and by calculating the statistical distribution of differences between the two (as shown in Figure 5). This analysis showed that there was close agreement between the two sources, and that the difference would tend to reduce the risk arising from any error.

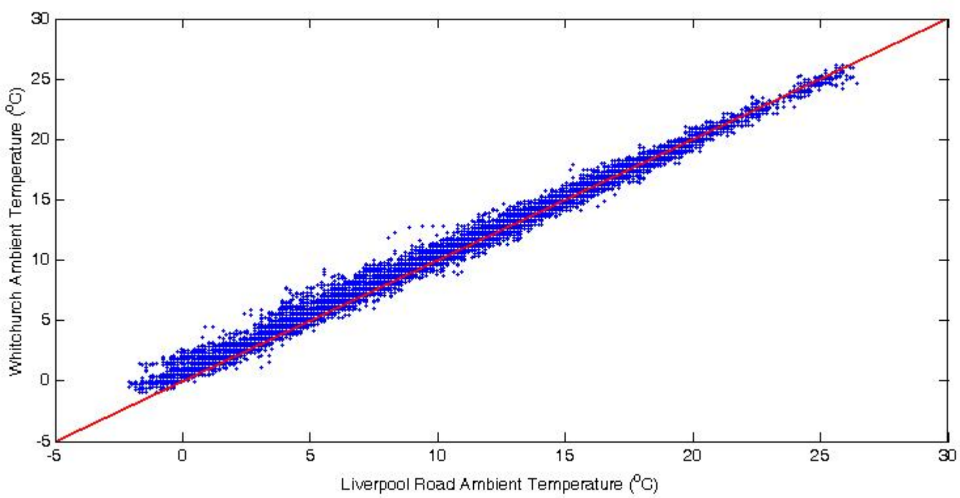

Figure 4: Point-by-point comparison of desired and potential substitute measurement

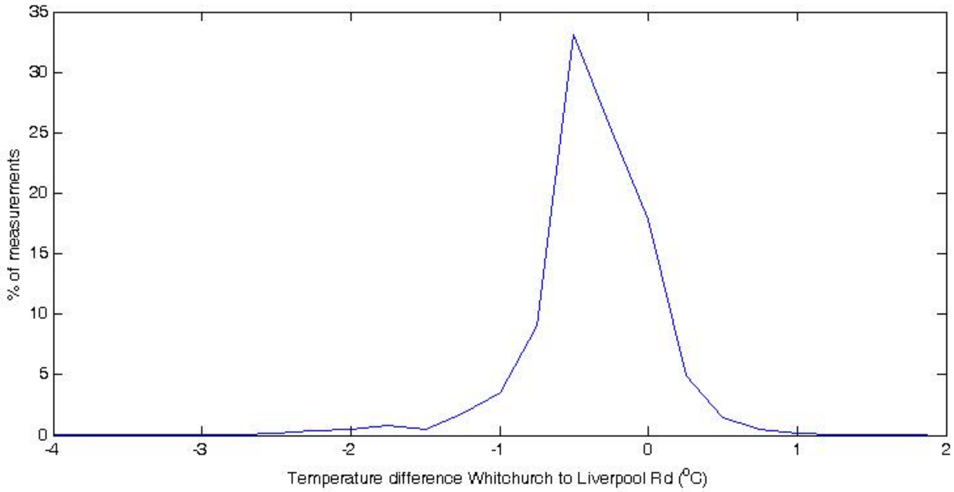

Figure 5: Statistical comparison of desired and potential substitute measurement

In other cases, it may be necessary to construct a replacement time series, either from average data taken from around the time of the missing data, or by selecting an appropriate alternative time series. Both of these approaches have been adopted for load measurement correction in analysis as part of the Flexible Networks project. An averaging approach was considered to be preferable, calculating a separate average profile for each day of the week, from several weeks around the missing measurements. However, this relies on the measurement series being sufficiently complete to permit calculation of a representative average.

In a second analysis, a simple averaging approach was considered to be impractical, since it was necessary for the substitute data to represent a change in network configuration during the period to be corrected, and also because of persistent measurement errors which cast doubt on ability to construct a representative average profile. In this case, therefore, the desired transformer load measurement was constructed by addition of appropriate substitute feeder and transformer measurement series which were selected by inspecting measurement series from the weeks surrounding the period to be substituted and averaging weekly series having the required ‘true’ measurements, and consistency with the observed values in the week of interest. An example is shown in Figure 6, in which the week of interest is coloured pale blue, and the substitute data is constructed by averaging weeks other than that week and the week shown in purple.

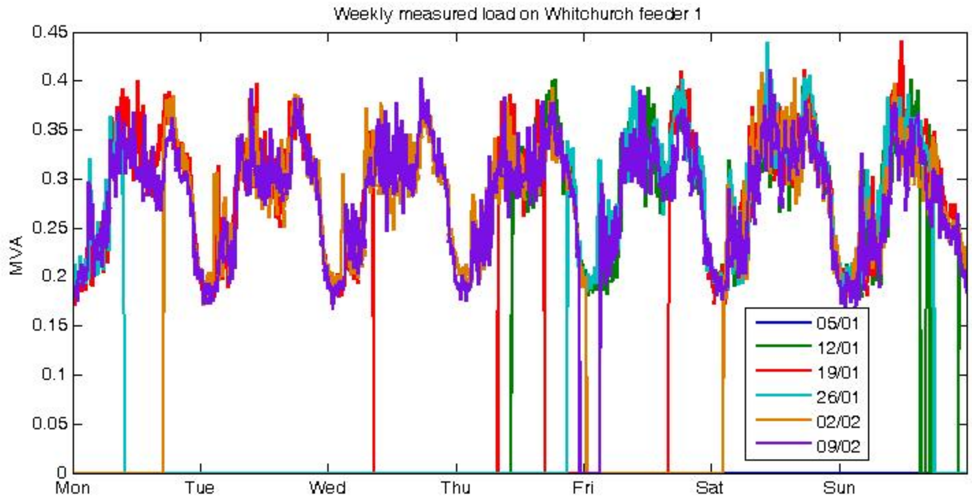

Figure 6: Identification and comparison of potential substitute data series

The resulting corrected load measurement series is shown in Figure 7.

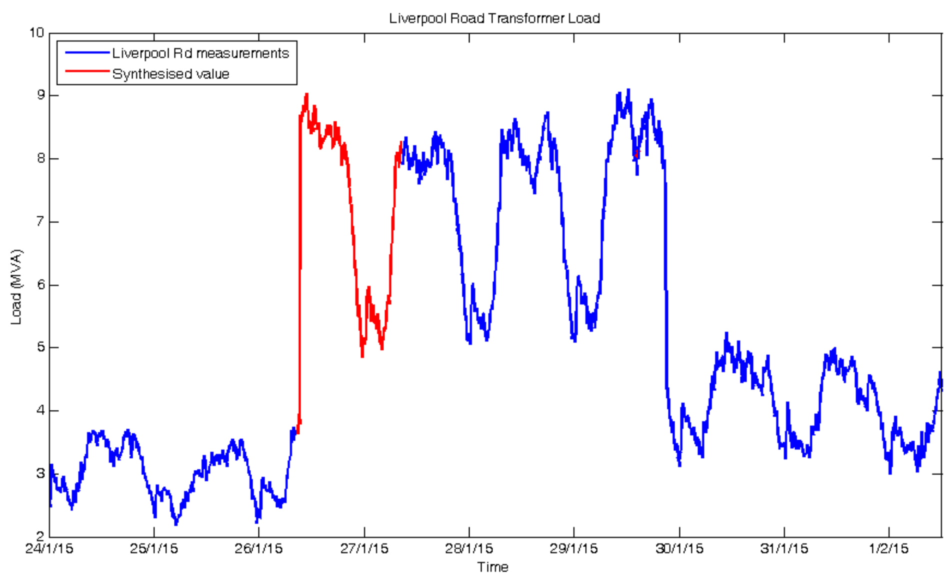

Figure 7: Data series including measured and corrected values

It should be noted that the large section of corrected data shown in red was considered suitable for use as part of a model conditioning process, in which modest errors would be acceptable in ensuring that the thermal state of the model was approximately correct. It was not considered to be reliable enough to be used in determining the state of the transformer thermal model during the time that it was compared with actual measurements.

In all cases it is important to note that corrected or substituted data points will usually be different from the 'true' measurement which would otherwise have been made. As such it is important that corrected data points are clearly identified, especially if they are placed in a long-term data archive, or are shared with users who are not involved in the gathering, validation and correction processes. This is necessary to ensure that the corrected data does not, over time, become regarded as a ‘true’ representation of actual measured behaviour of the measurand concerned, and be relied on inappropriately.

It is also important to document the precise method and data which has been used in the correction process. This will permit future analysts to determine the suitability of the correction method for the use of the data and to assess the risks which may result from it. An approach which is acceptable in large-scale statistical analysis may not be appropriate in cases where the detailed behaviour of the power system or its components over a short period is to be assessed.