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ADVANCES IN SELF-VALIDATING INSTRUMENTATION

Manus Henry[1], *Mihaela Duta*[1]

[1]Department of Engineering Science, University of Oxford, UK.

Abstract – This paper provides an overview into recent developments in self-validating sensors. This concept assumes the availability of internal computing power for self-diagnostics, and of digital communications to convey measurement and diagnostic data. A generic set of metrics are proposed for describing measurement quality, including on-line uncertainty. A SEVA instrument, based on the Coriolis mass flow meter is described; its ability to detect and compensate for the effects of two-phase flow has been implemented in a commercial meter. SEVA has been incorporated into a British Standard, which is currently being extended. Other related standardisation efforts include work by the European user organisations WIB and NAMUR, who are collaborating on an initiative to develop a common framework for describing sensor diagnostics on-line. Comparison with the SEVA Coriolis meter show some of the limitations of the WIB approach. Recent theoretical developments in SEVA include a simple technique for combining the outputs of redundant SEVA sensors for consistency checking and the calculation of a combined best estimate.

Keywords: self-validating sensors, sensor fusion, Coriolis mass flow metering.

1. THE SELF-VALIDATING SENSOR

The Sensor Validation Research Group at Oxford began in 1988 to examine the impact of digital technology on instruments, and to local fault detection in particular. It developed a theoretical model of how a 'self-validating' or SEVA instrument should behave [1]. This assumes the availability of internal computing power for self-diagnostics, and of digital communications to convey measurement and diagnostic data.

Currently, it is common for sensor diagnostics to be conveyed to the user via device-specific error codes (e.g. Fault 43 – coated electrode). While these codes are useful for maintenance purposes – the instrument technician knows what action is needed to correct the fault – this information is less useful for taking operational decisions. A plant with 10,000 sensors of 20 different types from 13 different vendors could face the generation of many thousands of different fault events, each of which needs to be interpreted from an operational point of view. For each potential fault event, can plant operation proceed, or must maintenance action be taken immediately?

The motivation behind the SEVA concept is to define a set of generic (i.e. plant- and instrument-

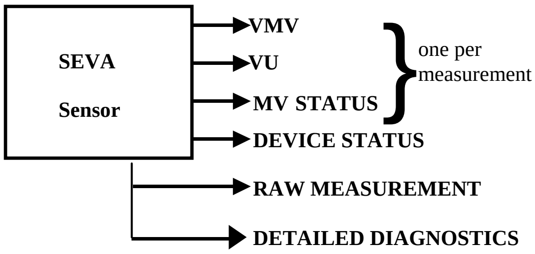

Fig. 1. Parameters from the SEVA sensor

independent) metrics for describing the quality of the measurement data, irrespective of the underlying fault mode (if any). This enables the development of generic strategies for responding to changes in measurement quality which do not need to interpret device-specific error codes.

A generic set of metrics are proposed for describing measurement quality (see figure 1). For each measurement, three parameters are generated:

- **The Validated Measurement Value (VMV)**. This is the conventional measurement value, but if a fault occurs, the VMV is a corrected best estimate of the true value of the measurand.
- **The Validated Uncertainty (VU)**. This is the metrological uncertainty, or probably error, of the VMV. For example, if the VMV is 4,31 l/s, and the VU is 0,05 l/s, then the sensor is claiming that the true measurement value lies between 4,26 l/s and 4,36 l/s with 95% confidence.
- **The Measurement Value Status (MV Status).** Given the requirement to provide a measurement, even with a serious fault, the MV Status indicates how the current measurement has been calculated. It takes one of a small set of values, of which the most important are:

  - SECURE: generated by redundant, fault-free sensors.
  - CLEAR: the measurement has been calculated normally.
  - BLURRED: live raw data is still being obtained, but the VMV has been corrected for some fault condition.
  - DAZZLED: a temporary state; it is known that current raw data is uncorrelated with the

true process variable (e.g. the input is saturated), but it is not (yet) known whether the condition is permanent. The VMV is projected from past history, and the VU increases with time to reflect the reduced confidence in this projected VMV.

- BLIND: like DAZZLED except that there is evidence to suggest that the loss of raw data is permanent.

The VMV, VU and MV Status are generated for each measurement output from the sensor. For example, many industrial sensors measure process temperature as well as (say) flow or pressure. The validity of each is distinct, and each will be affected by a fault in a different way. However, for maintenance purposes, a single Device Status parameter is also provided, which indicates the level of maintenance action currently requested by the sensor (None, Low, High, Critical), alongside any device-specific detailed diagnostics.

The most important indicator of measurement quality is the on-line uncertainty of each measurement, the VU. It is calculated based upon all error sources affecting the on-line measurement, including:

- The transduction - the mapping from the true process measurand to the observed transducer signal;
- The components used within the instrument;
- The characterization procedure at the end of the production line, and/or calibration procedures;
- The operating point, and process noise;
- The effect of any faults, whether instrument- or process-induced, after measurement compensation has been applied.

Thus the VU provides useful information about measurement quality whether or not a fault has occurred. By contrast, diagnostics are only provided in the (hopefully) rare occurrence of a fault, and describe only the nature of the fault and not its impact on measurement quality.

To summarize, SEVA maximizes the availability of the measurement by providing on-line correction for faults. It further provides an estimate of measurement quality in a standard, generic form, thus enabling operational and maintenance decisions to be taken based on application-specific criteria, without detailed knowledge of the sensor fault modes.

2. CORIOLIS MASS FLOW METER

SEVA can be viewed as a philosophy which promotes continuous measurement quality assessment and improvement. It has impact on all aspects of the sensor lifecycle (e.g. design, manufacturing, characterisation, installation, calibration), and not merely on-line operation. This is illustrated by the example of the Coriolis mass flow meter, which was the first instrument to undergo validation analysis [1]. Understanding of the fault modes fed into a redesign of the instrument, enabled by the continuous improvement in digital technology. The resulting instrument [2] has become a commercial product, Foxboro’s CFT-50. The use of all-digital technology has led to various performance improvements such as the dynamic response time of only 16ms [3]. However, a key feature is that the instrument is able to maintain operation in certain fault modes which are traditionally difficult for Coriolis mass flow meters.

Coriolis meters operate by vibrating a flowtube (typically 1-150 mm in diameter) through which the process fluid flows. Two sensors monitor the flowtube vibration. The frequency of oscillation (typically 50Hz - 1kHz) is used to calculate the density of the process fluid, while the geometry of the flowtube is so arranged that Coriolis forces act to give a phase difference between the two sensor signals which is proportional to the mass flow of the process fluid.

It is well-known that two-phase (gas/liquid) mixtures are very difficult for Coriolis meters to measure. A number of factors are at work, but typically, the high damping causes the flowtube to cease oscillation and hence no measurement is generated. This fault has industrial significance, for example in custody transfer applications where the meter may begin or end partially filled with air. The new meter developed by Oxford is able to maintain oscillation at any level of two-phase flow. However, the physics of two-phase flow inside a vibrating tube causes inertial losses leading to mass flow errors [4]. Detection and compensation techniques have been developed which provide improved measurement of two-phase flows. However, the uncertainty of the resulting corrected measurement (typically of the order of 2%) is inevitably greater than that for a single phase fluid (typically 0.2%). Hence the provision of on-line uncertainty information is valuable in quantifying the reduced measurement quality during two-phase flow conditions. Fig. 2 illustrates the performance of the SEVA Coriolis meter with two-phase flow.

Prior to the injection of two phase flow (at about 5s) the measurement status is CLEAR, and the uncertainty band around the measurement is small, at about

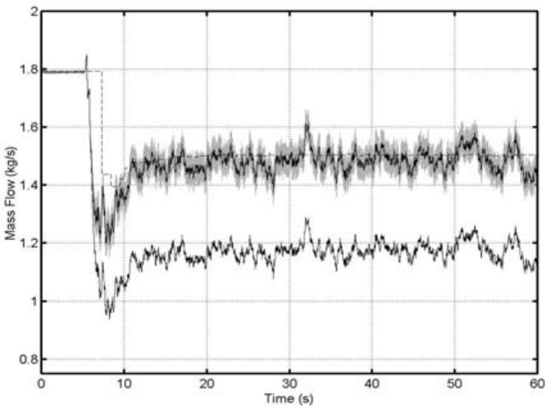

Fig. 2. Response of SEVA Coriolis mass flow meter to two-phase flow

0.2%. When air is injected into the process stream, the meter is able to maintain flowtube oscillation. The raw measurement (lower line) has an error of approximately 20%. Under the SEVA scheme the error is detected, the mass flow measurement is flagged as BLURRED, and a correction is applied. It can be seen from Fig. 2 that the corrected measurement (surrounded by uncertainty band) is a good approximation for the independently estimated true mass flow (dashed line). The uncertainty of the corrected mass flow ate is raised to approximately 2%. The generation of on-line uncertainty is valuable not only for taking on-line control or operational decisions, but also in assessing the overall uncertainty of a batch of metered product, for example in a custody transfer application.

3. SEVA STANDARDISATION ACTIVITY

In 1999 a survey was carried out by SIRA, funded by the UK's Department of Trade and Industry. It explored current and future requirements for field-busses, intelligent measurements and diagnostics among users and suppliers of flow measurement in the UK automation industry. It discovered a consensus on the need for a common standard for describing sensor diagnostics and measurement quality, and that the SEVA concepts were a suitable starting point. The survey recommended that a standard be developed by the British Standards Institute (BSI).

The first version of this standard (BS-7986) emerged in 2001 [5]. When the standard was discussed at the relevant IEC and Cenelec committees, comments were made regarding the compatibility of the validation concepts within the BSI standard and those of others, particularly Profibus and Fieldbus Foundation. Clearly, it is essential that validity data generated by field instruments can be conveyed through the digital communication systems to the control system. Accordingly, a revised draft of the BSI standard has been prepared, which is due for release shortly. The new version of the standard includes several amendments and additions, including:

- Validity metrics for discrete sensors such as proximity sensors;
- Validity metrics for analog actuators, such as valves;
- Informative comparisons of the use of validity data in the BSI standard, Fieldbus Foundation, PROFIBUS-PA and Mimosa.
- Informative explanation of the relationship between the BSI standard and the ISO/IEC GUM – the Guide to the use of Uncertainty in Measurement. This demonstrates that the SEVA concepts are a natural extension of the principles enshrined in the GUM.

4. VDI/VDE/NAMUR RICHTLINIE 2650

A number of European automation user organisations, including WIB and NAMUR, are co-operating to develop a common framework for specifying requirements for instrument diagnostics [6].

In Richtlinie 2650, specifications for two classes of diagnostics are given: those which are truly internal to the sensor (e.g. processor, memory or transducer errors), and those which arise in the immediate process environment (such as the interface between the transducer and the process). Part 1 gives general requirements, including definitions. Part 2 defines diagnostic requirements common to all instruments. Parts 3 and 4 give more specific diagnostic requirements for flowmeters and level sensing systems respectively. Further Parts will be added specifying requirements for other instrument types such as pressure, temperature sensors and valve positioners.

It is explained in Part 1 that manufacturers are expected to specify the functioning of each diagnostic method and to assign it a confidence level; users are expected to follow the installation and operational recommendations from the manufacturers. However, the interpretation of diagnostics for issues related to the process interface is left to the user.

Part 2 sets out diagnostics that all instruments are required to provide. These include checks on the transducer integrity and range, and basic electronic checks (range, checksum, watchdog timer, ADC and DAC verification, maximum electronic temperature).

In Part 3, diagnostics are listed for each of the common types of flowmeter along with the priority with which manufacturers are required to provide them. In the case of Coriolis mass flow meters, the following diagnostics are specified:

TABLE I. Diagnostics for Coriolis Meters (from [6])

Priority	Diagnostic condition
1	Gas bubbles in liquid
2	Fouling, clogging
2	Erosion, corrosion
3	False Mounting
4	Asymmetry of measuring tubes e.g. by plugging
4	External vibration
4	Pulsating flow
4	Partially-filled flowtube

It is clearly valuable to develop standards for diagnostics which are common between meters based on the same measurement technology – this reduces the 'error code complexity'. Nevertheless, if only diagnostic data is reported, without including consideration of measurement quality, this may be insufficient to usefully distinguish the performance of different meters. For example, the top priority diagnostic for coriolis meters as selected by the European user groups is the detection of gas bubbles in liquid, or two-phase flow, as discussed in section 2 above. However, there is an enormous difference in the performance of a conventional coriolis meter which stalls and ceases to operate when gas bubbles are present, compared with the performance of the digital Coriolis meter developed at Oxford which maintains operation, generates measurement data corrected for two-phase effects, and estimates the resulting uncertainty on-line.

A further issue that would appear not to have been addressed by Richtlinie 2650 is the fact that a single fault can have different effects on each of the measurements generated by an instrument. It is of course becoming increasingly common for a single instrument to generate multiple measurements (e.g. the process temperature along with the primary measurement); in the case of the Coriolis meter at least three measurements are generated – mass flow, density and process temperature. The impact of, for example gas bubbles, on each of these measurements is quite separate. The induced errors on mass flow and density are different, and under the SEVA scheme the uncertainty of the corrections are very different in magnitude. However, the temperature measurement is entirely unaffected by gas bubbles. These separate effects on each measurement are thus provided for in the SEVA scheme.

5. SEVA SENSOR FUSION

Although it is desirable to provide complete diagnostic coverage within an individual sensor, it is not economically or technically possible to ensure that all possible fault modes can be detected within the sensor itself. It is possible to use the SEVA metrics to perform higher level consistency checking between redundant SEVA sensors to detect faults that cannot be diagnosed in the individual sensors themselves [7].

Figure 3 illustrates the scenario. Three identical SEVA sensors, monitoring the same process measurand, generate VMV, VU and MV status values based on the limited diagnostics available at the local level. The combination block uses the SEVA data generated by each sensor to perform consistency checking between them, dealing with any outliers that are detected, and generating a Combined Best Estimate (CBE) of the true measurement value, along with SEVA metrics associated with this estimate.

There are of course many techniques that can be used for fusing data from multiple sensors. What is developed in [7] is a simple technique which requires no additional process modelling and which is suitable for implementation in a standard block such as might be used in an control system. All that is used are the properties of metrological uncertainty.

Thus, given n estimates x_i of the same measurand with uncertainties u_i , and assuming all measurements are judged to be consistent, then the combined best estimate of the measurement x* is given by:

$$x^* = \sum_{i=1}^{n} w_i x_i \quad \text{where } w_i = \frac{(\frac{1}{u_i})^2}{\sum_{j=1}^{n} (\frac{1}{u_j})^2} \qquad (1)$$

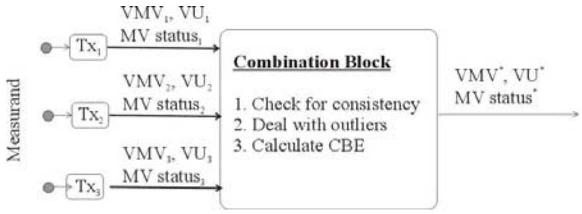

Fig. 3. SEVA Sensor fusion

while the uncertainty of x* given by

$$u^* = \sqrt{\sum_{i=1}^{n} w_i^2 u_i^2} = \frac{1}{\sqrt{\sum_{i=1}^{n} (\frac{1}{u_i})^2}} \qquad (2)$$

However, prior to combining measurements it is necessary to perform consistency checking. There is surprisingly little discussion of consistency between measurements with uncertainty estimates in the literature, but Moffat [8] suggests a calculation for two measurements only. This is based on a null hypothesis that the difference between the two measurements x_1 and x_2 should have zero mean. Using u_1 and u_2 to estimate the uncertainty of the difference, the test becomes a measure of a significant deviation from zero. Thus x_1 and x_2 are Moffat consistent if:

$$\left| \frac{x_1 - x_2}{\sqrt{u_1^2 + u_2^2}} \right| < 1 \qquad (3)$$

It can be shown [7] that if and only if equation (3) is satisfied, x*, the combined best estimate of x_1 and x_2 falls within the uncertainty bounds of both x_1 and x_2, an intuitively desirable result.

If the instantaneous measurements from two sensors fail the Moffat test, this does not necessarily imply that one or other of the sensors is suffering from a fault. For example, measurements drawn from normal distributions with the same mean and variance will fail the Moffat test with 5% probability due to random variation [7]. Any scheme for consistency checking needs to avoid generating large numbers of spurious alarms due to random jitter.

In order to identify which sensor is faulty, it is common to use at least three in a majority voting system. Assuming that faults are rare, and that random jitter is dealt with, the assumption is that if one sensor is inconsistent with the majority, then it is likely to be faulty.

Unfortunately, when extending consistency checking beyond two sensors, the Moffat test has a major limitation in that it is not transitive: if x_1 is consistent with x_2 , and x_2 is consistent with x_3, it does not follow that x_1 must be consistent with x_3. This is illustrated in Fig. 4: -1 ±1 is consistent with 0 ±1, and 0 ±1 is consistent with 1 ±1, but -1 ±1 is not consistent with 1 ±1.

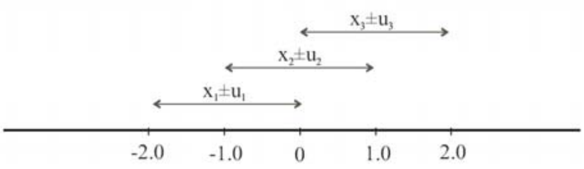

Fig. 4. Consistency is not transitive

Thus, given a set of 3 or more independent measurements that need to be combined, two issues need addressing. First, the maximum subset of mutually consistent measurements must be found and declared the consistent subset. Second, the measurements outside this subset, termed outliers, must be dealt with bearing in mind that inconsistency may be due to probabilistic jitter rather than sensor error.

It can be shown that the problem of finding the maximum subset of mutually consistent measurements is equivalent to the maximum clique problem in graph theory (Fig. 5). That is, given a set of nodes and arcs, find the maximum subset of nodes (called the clique) with the property that each node from the subset is connected to every other. If each node is a measurement and each arc is a consistency relation, then this is equivalent to the problem of measurement consistency checking.

The maximum clique problem is known to be NP-hard, requiring an exhaustive search to find the optimal solution. This can become extremely onerous as the number of measurements increases and the order of the maximum clique decreases. A method for approximating the maximum clique is proposed in [7] which uses overlapping intervals instead of the Moffat criterion to check for consistency. Because this method is linear in the number of measurements it has far less complexity than an exhaustive search. Moffat consistency is ensured at a later stage.

Once a maximum clique has been found, the obvious next step would be to use it to calculate the CBE using eqns 1 and 2 and to ignore all outliers. This approach has a number of difficulties:

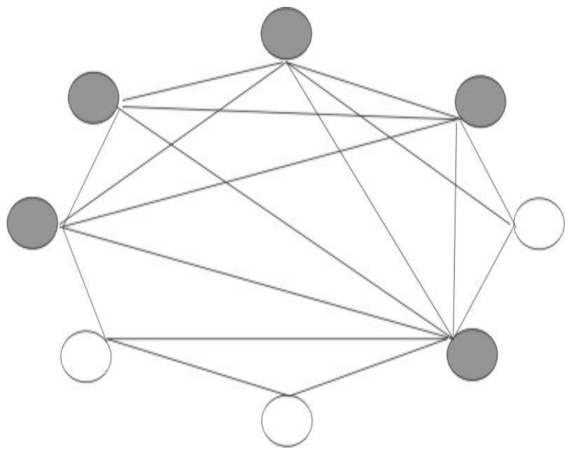

Figure 5. The maximum clique consists of the shaded nodes.

- Probabilistic jitter. As the number of inputs increases, the probability of all measurements being consistent reduces. For example, with 10 normally distributed measurements of equal variance and mean, there is only a 37.3% chance of all 10 sensors being mutually consistent at any given time.
- If, on average, one measurement is only marginally consistency with the rest, then sample by sample it may switch in and out of the consistent set. This will generate undesirable jitter on the CBE.
- It is possible that at any given time there may be more than one maximum clique. For example, in Fig 4, x_1 and x_2 are consistent, and x_2 and x_3 are consistent. It is not obvious which of the maximum cliques to use for calculating the CBE.

A simple strategy can be implemented to tackle these issues. The underlying idea is that any inconsistent measurement can be 'made consistent' by a sufficient increase in its own uncertainty, and that such an increase will cause a reduction in the weight of that measurement in the CBE. This approach is not based on uncertainty theory, but rather is a heuristic approach which has the desirable characteristics of smoothing over probabilistic inconsistency jitter, and providing a smooth reduction of weighting for inconsistent measurements. In the most general case when there is more that one clique, the measurements are partitioned into two sets:

- the **core set** - the intersection of all the maximum cliques
- the **peripheral set** - the rest of the measurements i.e. those being either in at least one of the maximum cliques, but not in the core set, or those outside any maximum clique

If the maximum cliques were found using exhaustive search, then the mutual Moffat consistency of the measurements inside it is ensured. However, this is not guaranteed to be the case with the linear search, thus, for the core and peripheral sets resulted from the linear search algorithm, additional uncertainty expansion may be required to ensure consistency.

5.1. Simulation Studies

Simulation studies of fusing up to 10 sensors are reported in [7]. It is demonstrated that the technique proposed is able to avoid false alarms due to probabilistic jitter while successfully detecting actual sensor faults. One example is shown in Figs. 6a and 6b. Three SEVA sensors measuring the same process parameter are monitored using a sensor fusion block. In this particular example a drift fault occurs in one of the sensors which is not detected by the sensor itself. Fig 6a shows the output of the faulty SEVA sensor, which from time t=100s incorrectly drifts upwards, away from the true measurement value while its MV status remains CLEAR. Fig. 6b shows the output of the combination block over the same time period. Initially the CBE also rises, but as the faulty meas-

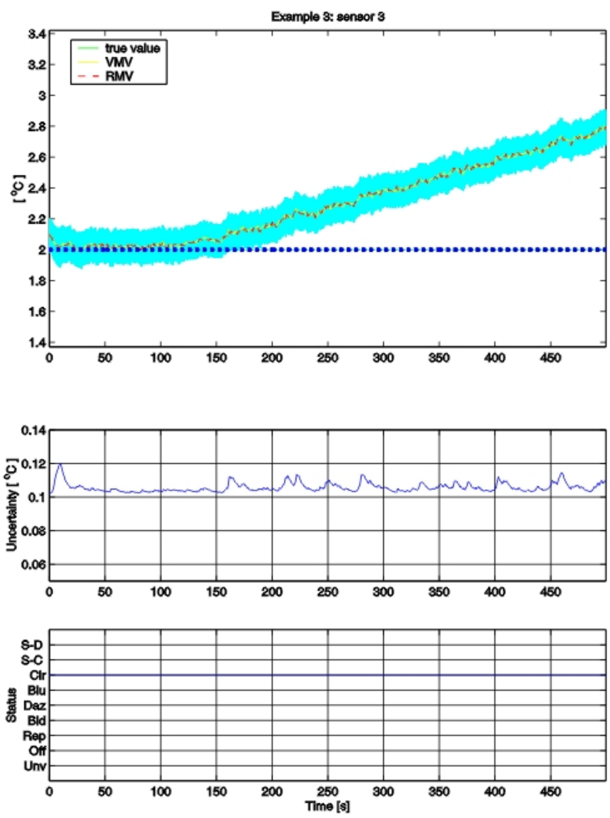

Fig 6a. Output of Faulty Sensor

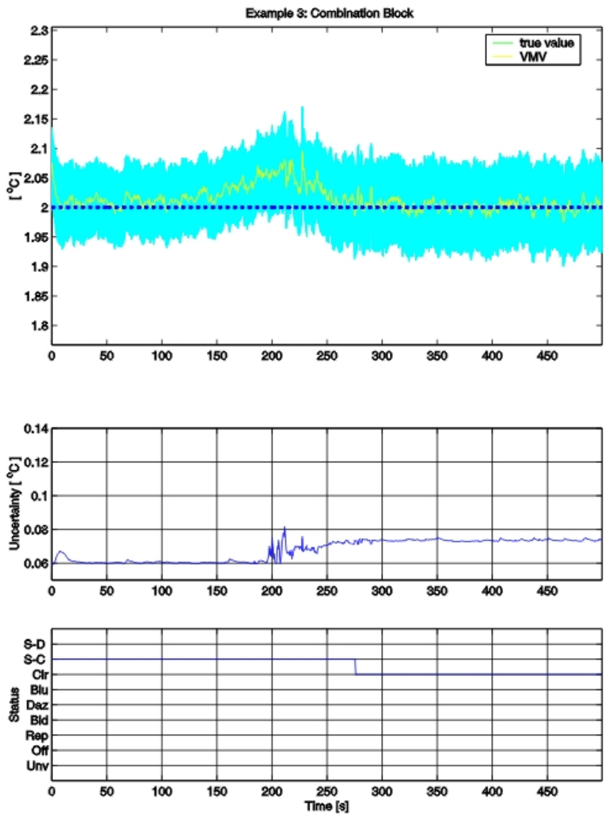

Fig 6b. Output of Combination Block

measurement drifts away from the measurements from the other two sensors (not shown) the CBE returns towards the mean of the fault-free sensors (from t=200s). While this is taking place the uncertainty of the CBE increases. Eventually, at t=275s, the output from the faulty sensor is sufficiently distant from the other measurements that it is labeled as permanently faulty, the CBE is based only on the non-faulty measurements and the MV status of the CBE is reduced from SECURE to CLEAR [7].

The combination block thus successfully detects the inconsistent measurement, and also generates a smooth transition in the calculation of the combined best estimate from using the data from all three sensors to that of only two.

6. CONCLUSIONS

This paper has discussed recent development in self-validating sensors, including a commercial coriolis mass flow meter, upcoming standards, and a new technique for performing consistency checking between SEVA sensors.

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Author(s): Dr. Manus Henry, Dr. Mihaela Duta, Department of Engineering Science, University of Oxford, Parks Road, Oxford, OX1 3PJ, UK. Phone: +44 1865-273913. Fax: +44 1865-273906. Email: manus.henry@eng.ox.ac.uk.