A Modified Parity Space Averaging Technique for Online Calibration of Redundant Sensors in Nuclear Reactors

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Abstract: Redundant sensors are usually used in nuclear reactors to measure critical variables and estimate their averaged time-dependent for maintaining safety and reliability of the reactor. Non-healthy sensors can badly influence the estimation result of the process variable. As online condition monitoring was introduced to enhance the reliability and maintainability of reactors, diagnosing the performance of redundant sensors online for the purpose of maintenance has become with high importance. Cross Calibration (CC) method is widely used to detect the anomaly of any sensor's readings among the redundant group. CC is a method that performs online averaging of redundant signals generating possible highly accurate estimation of the process variable and then compares each sensor signal with this estimate. Parity Space Averaging (PSA) technique is one of the averaging techniques used in CC method, it is used to weight the redundant signals based on their error band consistency. PSA assigns high weight to the signals that have shared bands, giving them weights regarding how many bands they share, and excluding the inconsistent signal from the averaging calculation by giving very low weight. EPRI has applied the parity space averaging in the Instrument Calibration and Monitoring Program (ICMP), thus, to enhance this technique, in this paper three methods are introduced for improving the PSA applied in the ICMP. The first was to add another consistency factor (so called Trend consistency TC) to consider to preserve the edge which can be a characteristic behavior or a real equipment fault of the process parameter. The second method proposed to replace the error band weighting factor (W^a) and the band consistency factor (C) by a weighting factor based on distance (W^d) and TC weighting factor, and the third method was to only replace W^d by W^a and apply it along with the TC and C. The redundant sensors underwent a preprocessing technique called Cross Moving Median (CMM) which can deal with noise, outliers, and missing data. Research reactor data sets were used to perform the validation of this method; four redundant hydrogen pressure transmitter signals (from S#1 to S#4) were obtained from the cold neutron source facility. Results regarding the ±3σ band showed that 2nd & 3rd modified approaches have rescannable improvement to the PSA technique.

Keyword: Redundant sensors, Parity Space averaging, Nuclear reactors.

1 Introduction

Redundant sensors usually used in nuclear power reactors and research reactors to measure plant conditions. Redundant sensors such as resistance temperature detectors (RTD), thermocouples, and pressure transmitters, etc., which are usually installed in reactors for checking critical variables and estimating their averaged time-dependent to assure reliable monitoring and control of the plant [1]. These sensors are subject to long-term exposure to heat, humidity, vibration, and other effects that can cause damage of the sensors' bonding, change in response time, or affect the measurement accuracy [2]. The degradation of these sensors is a major concern as they can give inaccurate records of the reactor's condition, especially in nuclear reactors where safety, reliability, productivity and maintenance cost are major concerns.

To ensure safe and reliable operation, calibration of safety related parameters' sensors in nuclear reactors is regularly performed once every fuel cycle. These calibration activities consume significant resources and time for isolating the instruments, calibrating them, and then returning them back for service. However, high quality sensors maintain accurate measurements for more than one or two years and, therefore, calibrating them would only mean wasting money [3][4]. Therefore, using performance based calibration rather than time based calibration led to the development of on-line drift monitoring and cross calibration techniques [2].

In the online Cross Calibration (CC) using averaging techniques, redundant sensor outputs are monitored during operation to identify the deviation of any signal with respect to the process parameter estimated average. If the sensor drifting outside acceptable limits [5][6], the sensor should undergo calibration or isolated and replaced as it can no longer be considered operable. This method is applicable to all types of process redundant sensors; it gives better approach for pressure, level, and flow transmitters [2].

The CC has mainly four well-known averaging techniques; the Straight Averaging, Band Averaging, Weighted Averaging, and Parity Space Averaging.

Straight Averaging (SA) is a simple averaging technique that doesn't consider weights for signals' points; it simply calculates the sum of redundant signals, and then compares each sensor signal to the average obtained. *Band Averaging* (BA) is an averaging technique involves applying an outlier band prior to the averaging process to eliminate outliers' effects on the estimated average. [3] *Weighted Averaging* (WA) and *Parity Space Averaging* (PSA) are averaging techniques based on weighting factors that can be calculated based on several methods; distance like in the WA, and error band and band consistency like in the PSA. Then each weighting value is multiplied to its corresponding estimated sensor's reading to obtain a reliable estimated average. [7][3][8]

Parity Space Averaging determines the consistency between redundant signals based on signals shared bands; the redundant measurements value combined with its measurements error band, the signals have shared bands are weighted as 2, 3, 4, etc., while any inconsistence signal's point that has no shared band with the any other signals' points is given 1. [9][5][3][7]

As to improve the calculations of the Parity Space Averaging, some factors such as characteristic edges should be considered. Edges in signal processing may indicate a transition between states or the occurrence of interesting/abnormal events [10]. that may tend to be a sign of equipment fault. These edges should be preserve in the calculation of the estimated average, to solve this problem, the similarity of the signals trend changes should be considered.

Hydrogen pressure data sets from the cold neutron source of a research reactor were used to perform the V&V as to compare the modified PSA approaches with the original Instrument Calibration and Monitoring Program (ICMP) approach.

These data underwent a preprocessing technique so called Cross Moving Median (CMM) which was introduced by the author in a previous publication. [11]

2 Methodologies:

Prior to implement the PSA as it was implemented in the ICMP and the modification approaches proposed by the author, the data was collected from the CNS of a research reactor was qualified by attenuating the noise and outliers, recovering the missing data, and generating an estimate for each sensor' signal. For this purpose, the Cross Moving Median, which was proposed by Kassim & Heo [11], was used to remove the bad data. The CMM method is a method based on the moving median filter but it considers the immediate past estimate to recover the missing data. Avoiding the prolongation, it is not necessary to repeat the details of the CMM filter here in this paper.

2.1 Parity Space Averaging (PSA):

As in the EPRI report [5]; the ICMP applied the Parity Space method as determining the consistency between redundant signals and signals weights based on the error bands, obtaining two weighting factors; the accuracy weighting factor (W^a) and the band consistency weighting factor (C).

W^a was calculated as in the ICMP using the sensors accuracy rather than the error bound since the accuracy of an instrument is sometimes equal to its signal error bound in equation (1):

$$W_k^a(i) = \frac{1}{A^2} \quad (1)$$

Where; A is the accuracy of the signal's sensor,

$$i = 1, 2, 3, \ldots, n,$$

and n is the sample length of the filtered signal (S).

In this study, since the accuracy of each sensor is unknown, it is determined to use the Confidence Interval (CI) instead. CI is a quantified limits of uncertainty degree around common parameter of interest, this limits add a margin of error to the parameter. [12] The degree of 95% confidence Interval (CI) is given [13] as bellow:

$$95\%CI_k(i) = S_k(i) \pm 1.96\left({}^{\sigma_{S_k}}/_{\sqrt{n}}\right) \quad (2)$$

Where σ is the standard deviation of the filtered sensor (S),

and $k = 1,2,3 \ldots, m$.

The weighting factor C was given natural numbers considering how many bands a signal is sharing with other signals, as following:

$$C_k(i) = \begin{cases} 1 & ,if\ \ no\ \ shared\ \ bands \\ 2\ ,if\ \ 2\ \ signals\ \ shared\ \ a\ \ band \\ 3\ ,if\ \ 3\ \ signals\ \ shared\ \ bands \\ \quad . \\ \quad . \\ m\ ,if\ \ m\ \ signal\ \ shared\ \ bands \end{cases} \quad (3)$$

Where m is the redundant signals number.

If any of the redundant signal band is not sharing any other signals bands, the band consistency weighting factor will be 1 as to be given the lowest weight. And if the other cases it will be given 2 if tow signals share the bands, and will be given 3 if three signals share the bands and so on. Then the estimated average was calculated in the ICMP as in equation (4):

$$\hat{S}(i) = \frac{\sum_k^m W_k^a(i) \times C_k(i) \times S_k(i)}{\sum_k^m w_k^a(i) \times C_k(i)} \quad (4)$$

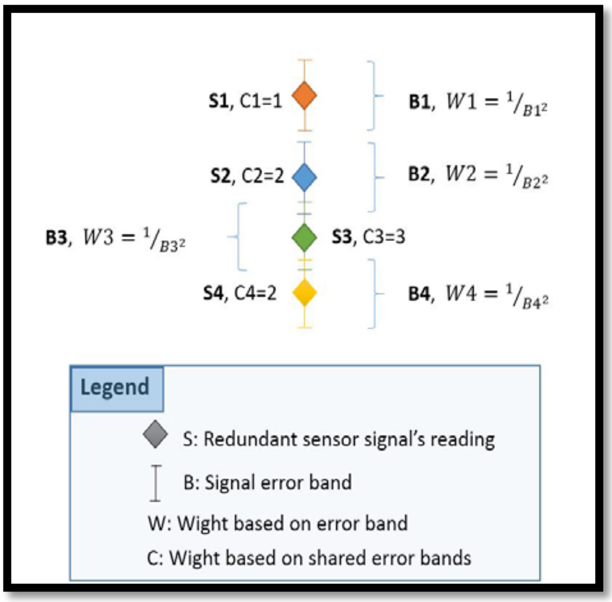

Figure 1. Parity Space Averaging technique as implemented in the ICMP

2.2 Modifying approaches:

As to consider the dynamic trend consistency in the calculation of the PSA, and as it is shown in figure (1), three approaches were mainly applied to improve the Parity Space Averaging technique:

A. 1st approach: *Adding the Trend Consistency (TC) to the PSA calculation as in the ICMP.*

The dynamic Trend Consistency can be calculated using the edge localization approach in the Edge Detection method (ED) [10]. For applying this approach, the numerical central difference was calculated as in equation (5); as following:

$$\frac{d^2 S_k}{d^2 t} = S_k(i+1) + S_k(i-1) - (2 \times S_k(i)) \quad (5)$$

The localization of an edges will show the local minima as a negative value, the local maxima as a positive value, and the unchanged behavior as zero. Then if all redundant signals were showing local maxims or all of them are showing local minims, there should be a characteristic edge or abnormal behavior in the signal of the process parameter. As to deal with this case, the TC weighting factor should be involved in the calculation, and for this purpose the TC will be also given natural numbers as following:

$$TC_k(i) = \begin{cases} 1 & ,if\ no\ trend\ similarity \\ 2 & ,if\ 2\ signals\ has\ same\ trend \\ 3 & ,if\ 3\ signals\ has\ same\ trend \\ & . \\ & . \\ m, & if\ m\ signals\ has\ same\ trend \end{cases} \quad (6)$$

If all signals behaviors show either a positive trend, negative trend, or no change trend at the same time, TC will be at its maximum number (m). While if only some signals are showing similar trend behavior the TC weight will be determined based on the number of signals showing same trend; if three are in positive trend, TC will be equal to 3, and so on.

Adding this weighting factor to the ICMP calculation, equation (4) will be upgraded as following:

$$\hat{S}(i) = \frac{\sum_k^m W_k^a(i)\times C_k(i)\times TC_k(i)\times S_k(i)}{\sum_k^m w_k^a(i)\times C_k(i)\times TC_k(i)} \quad (7)$$

B. **2nd Approach:** *Adding the Trend Consistency (TC), eliminating the band consistency (C), and changing W to be based on Euclidian distance rather than accuracy.*

When sensor accuracy is unavailable, and the error bound cannot be fully calculated, the weighting factor $\boldsymbol{W^d}$ can be calculated based on the Euclidian distance and the set complement as it was proposed by Kassim & Heo [8]. And as no need to explain the calculation of W based on the Euclidian distance here again, the equations (8, 9, 10, 11) are stated below:

$$d_z(i) = \sqrt{\sum_{k=1,k\neq z}^m (\hat{S}_z(i) - \hat{S}_k(i))^2} \quad (8)$$

$$\bar{d}_z(i) = \left(\sum_{k=1}^m d_k(i)\right) - d_z(i) \quad (9)$$

$$\bar{d}_{sum}(i) = \sum_{k=1}^m \bar{d}_k(i) \quad (10)$$

$$W_k^d(i) = \bar{d}_z(i) \Big/ \bar{d}_{sum}(i) \quad (11)$$

Where; d_z is the Euclidian distance of a sensor's signal with respect to all other sensors' signals.

$\bar{d}_z$ is the set complement of d_z,

z is any signal of the redundant group,

and $\bar{d}_{sum}$ is the summation of all $\bar{d}_z$.

Fault isolation test that was implemented by Kassim & Heo [14] was not considered here in this study, which mean that that weighting factor W^d will not be equal to zero.

When calculating the weighting factor W^d based on Euclidian distance there should be no need to use the band consistency weighting factor in the calculation of the estimated average unless we want to emphasize the importance of the band consistency.

Therefore, after implementing the weighting based on Euclidian distance instead of the one used in the ICMP, and eliminating the band consistency weighting factor, the estimated average can be calculated as following:

$$\hat{S}(\boldsymbol{i}) = \frac{\sum_k^m \boldsymbol{W_k^d(i)\times TC_k(i)\times S_k(i)}}{\sum_k^m \boldsymbol{w_k^d(i)\times TC_k(i)}} \quad (12)$$

C. 3rd Approach: *Adding the Trend Consistency (TC), keeping the band consistency (C), and changing W^a to be based on Euclidian distance (W^d) rather than accuracy.*

Here in this approach, we assume that emphasizing the band consistency has equal importance as implementing the trend consistency and it should be kept in the calculation of the estimated average. Thus, equation (13) will be written as:

$$\hat{S}(i) = \frac{\sum_k^m w_k^d(i)\times C_k(i)\times TC_k(i)\times S_k(i)}{\sum_k^m w_k^d(i)\times C_k(i)\times TC_k(i)} \quad (13)$$

2.3 Decision metrics:

As generating a reliable estimated average in this study, it is important to explain the limits and the index that the operator and maintenance staff would decide the sensor healthy condition upon.

2.3.1 Deviation limits:

Mainly the Maximum Acceptable Value of Deviation (MAVD) and Allowable Deviation Value for On-Line Monitoring (ADVOLM) are the conservative limits that are used to identify the onset of a drift problem. These limits should be specified by a licensee and supported with a technical basis [15]. However, and since it is not possible to have all uncertainty components of the ADVOLM and the MAVD, two decision limits were used to check the healthy condition of any sensor among the redundant group. These two limits are:

- **Prediction Interval (PI):**

Dealing with redundant signals, the Prediction Interval (PI) is used to determine the uncertainty band instead of the confidence interval that is used for nonredundant signals, this interval includes the model prediction's variance, the model bias error, and the noise variance [16] [17] [18], as in equation (12):

$$95\%PI(i) = \hat{S}(i) \pm 1.96\sqrt{MSE + \left(\sigma_{\hat{S}} \Big/ \sqrt{n_{\hat{S}}}\right)^2} \quad (12)$$

Where $\hat{S}$ is the estimated average of redundant sensors,

$\sigma_{\hat{S}}$ is the standard deviation of the estimated average sample,

and $n_{\hat{S}}$ is the sample population of the estimated average .

MSE is the mean square root error that can be calculated by the following equations:

$$MSE = {}^{1}/_{n}\sum(S_{avg}(i) - \hat{S}(i))^2 \quad (13)$$

Where;

$$S_{avg}(i) = \sum_{k=1}^{m} S_k(i) \quad (14)$$

- **The $\pm 3\sigma$ Band:**

Like in the Z-score method [19], a statistical band can be set to identify any faulty data with respect to the signal's entire range using the standard deviation (σ). And since as dealing with samples ranges more than 30 points of a steady state data of nuclear reactor, the approach of using the dynamic band of $\pm 3\sigma$ can be reasonably applied in this study, too. The maximum and the minimum limits are calculated as following:

$$Max\hat{S} = \hat{S}(i) + 3\sigma_{\hat{S}} \quad (15)$$

$$Min\hat{S} = \hat{S}(i) - 3\sigma_{\hat{S}} \quad (16)$$

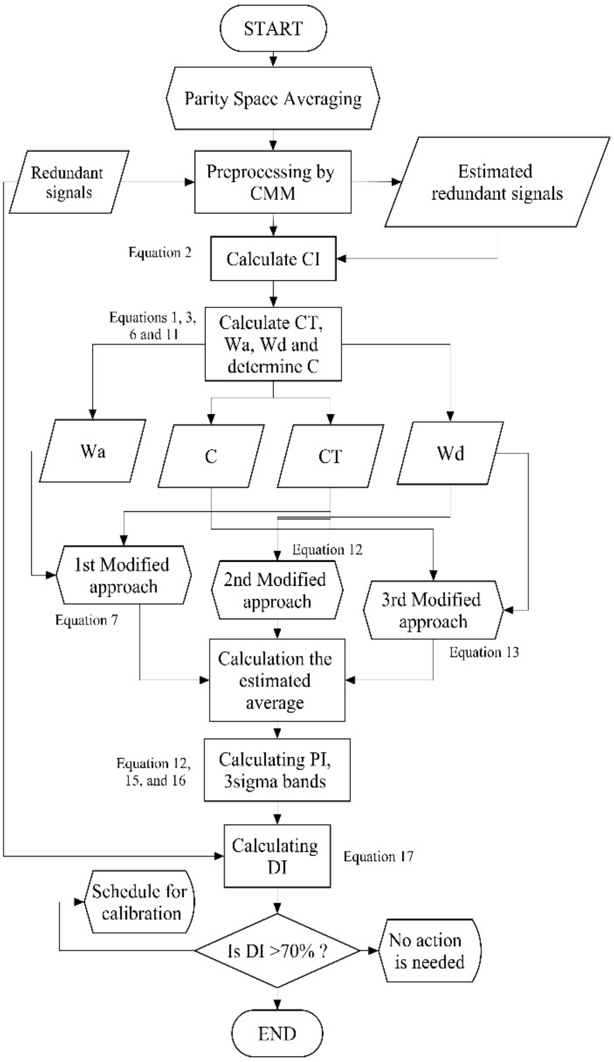

Figure 2. Procedures of the modified Parity Space Averaging approaches

As shown in fig. 2, before starting with generating the weighing factors $\boldsymbol{W^a}$, *C*, $\boldsymbol{W^d}$, and *TC*, the preprocessing CMM technique was implemented, and then the confidence interval (CI) of each sensor was calculated which was used for calculating the weighting factor based on accuracy (or signal error margin), and the same CI was used to determine the band consistency factor C. and as it was explained previously, the weighting factor based on Euclidian distance was determined using equation (11), while the trend consistency factor was determined using equations 5 and 6.

The four approaches including the ICMP approach

were performed separately to generate the estimated average vector, and then the Prediction Interval (PI) was applied to the estimated average.
For checking the healthy condition of each sensor, each sensor was separately compared with the estimated average vectors generated by the four approaches, and then the Drift Index (DI) was calculated as the decision measure of sensors' health condition.

2.3.2 Drift Index (DI):

As this algorithm can be implemented on-line, the need of a metric decision parameter that can summarize the drift of any sensor's signal from the estimated average after certain time is good as to show a quantifying decision measure.

The Drift Index (DI), in equation (17), can show the number percentage of signal's points that present inside the uncertainty bands of interest with respect to the total numbers of sample points, as follow:

$$DI\_S_k = \left({}^{\#(S_k(i) \in [U])}\big/_{(n)} \right) \times 100 \qquad (17)$$

Where U is the uncertainty band of interest which can be $\pm 3\sigma$band, or PI.

3 Results & Discussion

Data sets, which were generated from the cold neutron source of a research reactor for a hydrogen pressure in steady state normal condition and shutdown condition, were used to verify and validate the three modification approaches with respect to the ICMP approach.
And, in figure (3), the estimated averages of all four approaches are illustrated, and it can be noticed that although the ICMP approach and the 1st modified approach shows more steady state then others, it gives lower estimation than all sensors' signals, while the 2nd and the 3rd approaches show reasonable estimation, especially the 3rd approach. It can be inferred here, that the W^d factor was the dominant weighting factor that can enhance the results of PSA, while the C factor is still needed to bring the estimated average to the middle between the ICMP and 2nd modified approach.

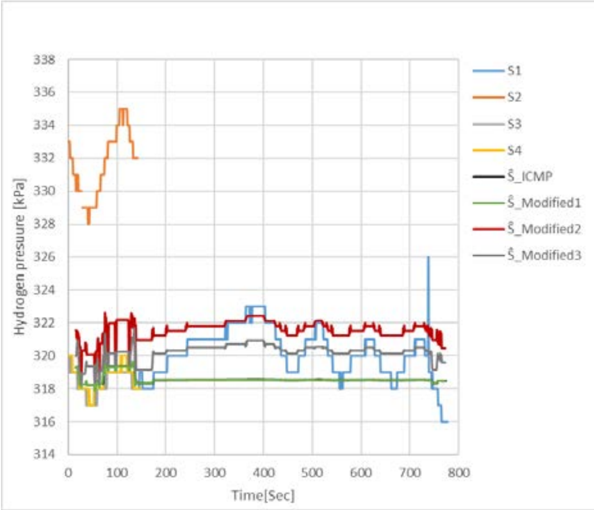

Figure 3. Estimated average vectors as generated using ICMP, 1st, 2nd, and 3rd approaches

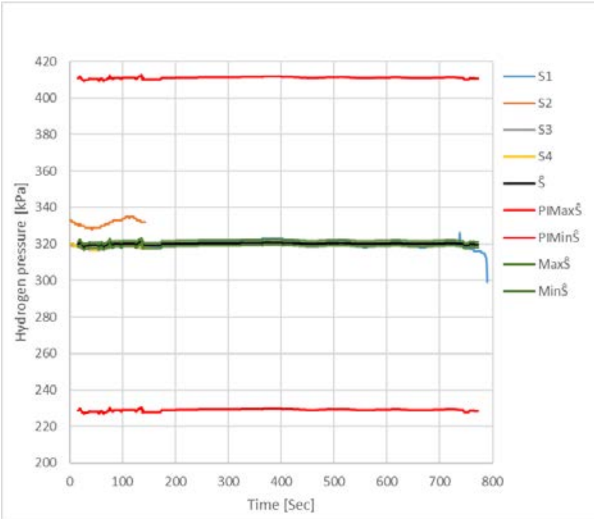

Figure 4. PSA results of the 2nd modified approach for the hydrogen pressure in normal steady state condition

In the normal operation condition as shown in table (1), the PSA method was enhanced a little by adding CT weighting factor in the modified approach#1 especially if we look at the results regarding the ±3σ band. For the modified approache#2 and #3, the parity space averaging was clearly enhanced by replacing the weighting factor W^a based on CI band (error band or accuracy) by the weighting factor W^dbased on Euclidian distance, where the Euclidian distance index can provide accurate weight as the more the redundant signal is near to the other redundant signals, the more weight it will be given. In figure 4 & 5, the modified approach#2 and the modified

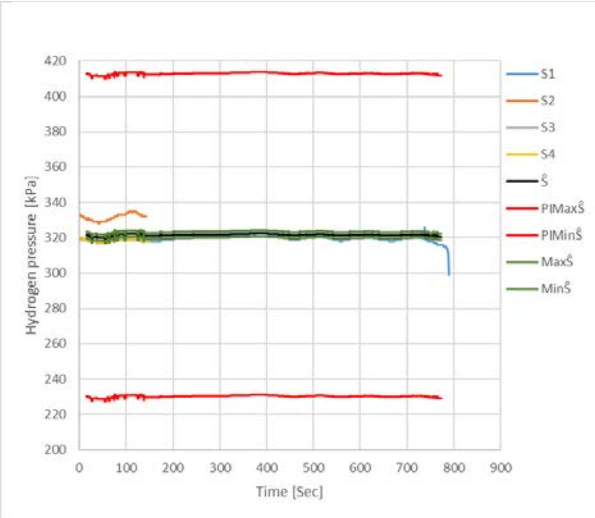

Figure 5. PSA results of the 3rd modified approach for the hydrogen pressure in normal steady state condition

approach#3 results which are mainly based on Euclidian distance are illustrated.

It can be seen that the PI is very big to identify any unacceptable deviation from any sensor of the redundant group. But the ±3σ showed clearly that Sensor number 2 (S#2) is located outside the band and it doesn't have a normal shift, it has a zero shift problem [20] [5].

As in S#2, a long ranges of S#3, and S#4 are missing. While S#1 generally showed acceptable fluctuation in the ±3σ band.

Likewise, the four PSA methods were applied on a shutdown condition of the same Hydrogen pressure redundant transmitters, and the DI results as stated in table (2) also showed that the modified approache#2 and the modified approach#3 gives better results.

Table 1. Drift Index decision results for hydrogen pressure redundant signals of normal operation condition as obtained from 4 PSA methods

Decision Limits	Averaging Methods	DI_{S1} %	DI_{S2} %	DI_{S3} %	DI_{S4} %
PI	PSA in ICMP approach	98	16	16	16
	Modified PSA approach#1	98	16	16	16
	Modified PSA approach#2	98	16	16	16
	Modified PSA approach#3	98	16	16	16
±3σ	PSA in ICMP approach	37	0	11	15
	Modified PSA approach#1	36	0	11	14
	Modified PSA approach#2	56	0	2	2
	Modified PSA approach#3	83	0	11	13

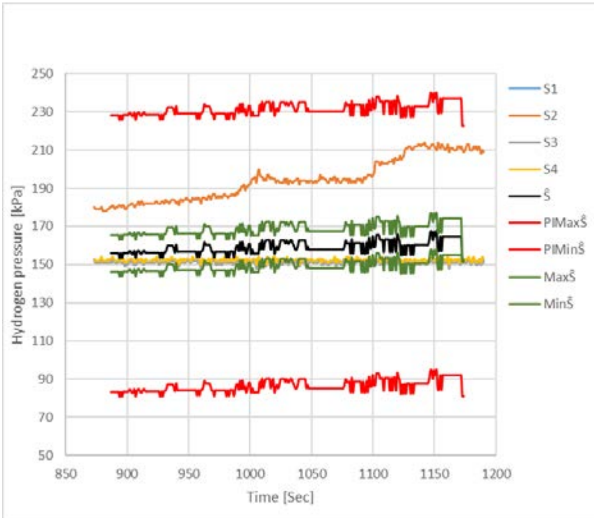

Figure 6. PSA results of the 2nd modified approach for the hydrogen pressure in shutdown condition

In figure 6 & 7, the ±3σ band identified S#2 as out of the estimated average band while most of the other sensors (S#1, S#3, and S#4) are inside.

The PIs in both 2nd and 3rd modified approaches are still very big that no sensor's signal shows drifted outside, but it can be inferred from the trend of S#2 that it is going to exceed the PI sometime later. Other sensors' signals are showing acceptable behavior inside the PI.

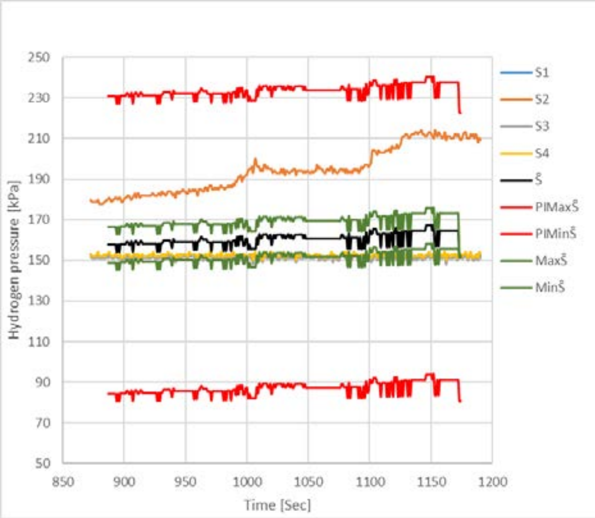

Figure 7. PSA results of the 3rd modified approach for the hydrogen pressure in shutdown condition

Table 2. Drift Index decision results for hydrogen pressure redundant signals of shutdown condition as obtained from 4 PSA methods

Decision Limits	Averaging Methods	DI_{S1} %	DI_{S2} %	DI_{S3} %	DI_{S4} %
PI	PSA in ICMP approach	99	100	99	99
	Modified PSA approach#1	99	100	99	99
	Modified PSA approach#2	99	100	99	99
	Modified PSA approach#3	99	100	99	99
±3σ	PSA in ICMP approach	45	0	33	39
	Modified PSA approach#1	46	0	33	40
	Modified PSA approach#2	55	0	49	62
	Modified PSA approach#3	75	0	70	78

4 Conclusion

As the redundant sensors are very important instruments in the nuclear reactors and since they are providing signals of the safety related parameters in the reactor, they should be monitored online to check any unhealthy behavior on time.

The online monitoring Cross Calibration (CC) is widely used to provide an estimated average signal of the redundant signals, however, it is still very important to improve the CC averaging techniques as to provide more reliable estimate. The parity Space Averaging technique is one of the CC averaging techniques, it accounts for the error band in term of weighted average. Weighting factor based on the error band or accuracy is used alone with another weighting factor based on bands consistency. The ICMP has implemented the PSA technique using the accuracy (W^a) This instead of the error bounds, however, in this study, the Confidence Interval (CI) was used to calculate the error bounds instead.

This study, provided three modification approaches that can enhance the output of the PSA, involving two new weighting factors; W^d which is a weighting factor based on Euclidian distance, and TC which is a weighting factor based on dynamic trend consistency.

The results as illustrated in this paper, showed that the 2nd and the 3rd modified approaches are giving a real contribution in the enhancement of the estimated average. The results also showed that regarding the ±3σ band, sensor#2 has a zero shift problem in addition to a long range of missing data problem, while S#3, and S#4 only a long range of missing data problem. And all approaches with respect to all decision limits applied in this study showed that S#1 is a reliable healthy sensor.

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