

Signal Validation for Flexible Operation of Nuclear Power Plants Using a Temporal Convolutional Autoencoder

Jiyong Lee^a, Jonghyun Kim^{a*}

^aDepartment of Nuclear and Quantum Engineering, Korea Advanced Institute of Science and Technology (KAIST) 291
Daehak-ro, Yuseong-gu, Daejeon, 34141, Republic of Korea

*Corresponding author: jonghyun.kim@kaist.ac.kr

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1. Introduction

As renewable generation grows, nuclear power plants (NPPs) are increasingly required to perform flexible load-following operation rather than remain at rated power. During such maneuvers, reactor power and coupled process variables vary over a wide operating range, making it more difficult to distinguish sensor degradation from legitimate process changes than under base-load operation.

Sensor calibration in NPPs is traditionally performed during refueling outages, allowing in-cycle drift to remain undetected while normal sensors may be recalibrated unnecessarily. Online monitoring (OLM) addresses this issue by reconstructing the expected response of each variable from correlations among process variables [1,2]. Most demonstrations, however, have focused on steady operation near rated power. Conventional residual monitoring uses a fixed threshold, which has two inherent limitations: transient residual fluctuations can cause false alarms unless the threshold is relaxed, while drift that remains slightly below the threshold may never be detected because each sample is evaluated independently and persistent evidence is discarded. Since incipient drift can also be comparable to noise, sequential evidence accumulation is needed for reliable detection [3].

This paper presents a signal-validation framework for load-following operation based on a temporal convolutional network autoencoder (TCN-AE) and a sequential probability ratio test (SPRT), validated using real plant data. The TCN-AE reconstructs expected signal behavior under changing operating conditions, while the SPRT detects persistent deviations in the reconstruction residual. Section 2 describes the two methods, Section 3 the signal-validation procedure, Section 4 the experiments, Section 5 the drift-detection results, and Section 6 concludes.

2. Method

The framework follows the standard OLM structure, in which a reconstruction model estimates the expected value of each monitored channel and a decision procedure evaluates the residual. The TCN-AE reconstruction model and SPRT-based decision logic are described below.

2.1 Temporal convolutional network autoencoder

Let $x(t) \in R^m$ denote the normalized measurement vector at time t . Using a sliding window of length L , the model input is constructed according to Eq. (1):

$$X(t) = [x(t - L + 1), \dots, x(t)] \in R^{L \times m} \quad (1)$$

The encoder-decoder pair maps the input sequence to a latent representation and reconstructs it, as in Eq. (2):

$$z(t) = f\theta(X(t)), X(t) = g\theta(z(t)) \quad (2)$$

The TCN-AE is trained on Normal sequences by minimizing the mean-squared reconstruction error defined in Eq. (3):

$$L_{rec} = \frac{1}{Lm} \sum_{i=1}^L \sum_{j=1}^m (X_{ij}(t) - \hat{X}_{ij}(t))^2 \quad (3)$$

Both the encoder and decoder are constructed using causal, dilated one-dimensional convolutions [4], as shown in Fig. 1. Causal convolution ensures that each output depends only on the current and preceding samples, while dilation expands the receptive field efficiently. Among autoencoder architectures, the TCN-AE is particularly suited to flexible operation: unlike static fully-connected autoencoders, which capture only instantaneous cross-variable correlations valid near a single operating point, it models the temporal evolution of the signals, so a load-following maneuver is reconstructed as a normal trajectory rather than flagged as an anomaly. TCN-AE suits continuous real-time monitoring. Trained exclusively on normal operating data, the TCN-AE learns temporal and cross-variable relationships among the measured signal.

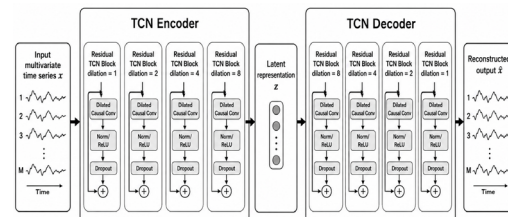


Fig. 1. Concept of the TCN-AE with dilated convolutions.

2.2 Sequential probability ratio test

The SPRT [3] accumulates evidence sample rather than evaluating each residual independently. Let $RE(t)$ denote signed reconstruction error defined in Section 3. Under the null hypothesis H_0 , $RE(t)$ follows a zero-mean Gaussian distribution with standard deviation σ , whereas the alternatives $H_1 \pm$ shift its mean by $\pm M$, as in Eq. (4).

$$\begin{aligned} H_0: RE(t) &\sim N(0, \sigma^2), \quad H_1 \pm: RE(t) \sim N(\pm M, \sigma^2), \\ \Lambda \pm(t) &= \Lambda \pm(t-1) + \left(\frac{M}{\sigma^2}\right) \left[\pm RE(t) - \frac{M}{2}\right], \\ A &= \ln[(1-\beta)/\alpha], \quad B = \ln[\beta/(1-\alpha)] \end{aligned} \quad (4)$$

A positive (negative) drift is indicated when $\Lambda^+(t) \geq A$ ($\Lambda^-(t) \leq B$). When either statistic falls below B it is reset to zero for continuous monitoring. The target magnitude is $M = k\sigma$, where k sets the sensitivity relative to the nominal residual variation, and a persistence criterion N_{run} declares a drift only when same-direction indications persist for N_{run} consecutive samples. Because reconstruction residuals are autocorrelated, the Wald boundaries derived for independent Gaussian residuals make α and β nominal design values; the empirical false-alarm behavior is verified on held out normal data, with persistence as an additional safeguard as shown in Fig. 2.

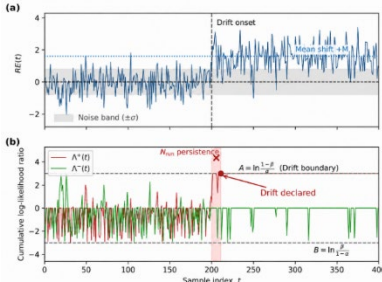


Fig. 2. Two-sided SPRT-based drift detection logic: (a) signed RE and (b) cumulative log-likelihood ratios.

3. Signal Validation OLM

The proposed OLM framework combines TCN-AE reconstruction with SPRT-based decision logic for sensor drift detection during load-following operation. As shown in Fig. 3, the procedure consists of four steps: 1) input preprocessing, 2) signal reconstruction, 3) RE calculation, and 4) sensor state determination.

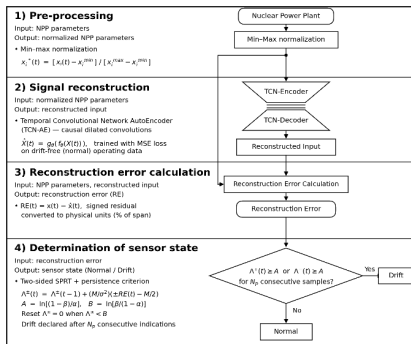


Fig. 3. Signal validation procedure.

3.1 Input preprocessing

Process variables span different ranges and units, and variables with larger magnitudes would dominate the loss and drive the network toward a poor local minimum. Variable-wise min-max normalization based on the training data is therefore applied, as in Eq. (5).

$$x_i^*(t) = \frac{x_i(t) - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, \quad i = 1, 2, \dots, m \quad (5)$$

3.2 Signal reconstruction

The normalized signals are reconstructed by the TCN-AE of Section 2.1. The encoder compresses their temporal dynamics into a latent representation, and the decoder reconstructs an output as similar to the input as possible, the causal dilated convolutions capturing the time-series dependencies of the dynamic plant signals.

3.3 Reconstruction error calculation

The RE is defined as the signed discrepancy between the measured and reconstructed signals at the most recent step, as expressed in Eq. (6), converted to physical units through the observed range of each variable so thresholds can be stated in instrument-span percentages

$$RE(t) = x(t) - \hat{x}(t) \quad (6)$$

Under normal behavior, $RE(t)$ fluctuates near zero, whereas developing drift produces a persistent shift whose sign follows the drift direction.

3.4 Sensor state determination

A simple instantaneous rule declares drift when $|RE(t)|$ exceeds a predefined threshold τ , as in Eq. (7), but it is sensitive to short noise fluctuations: a tight threshold produces false alarms, a loose one delays detection. The two-sided SPRT of Section 2.2 is therefore applied to each variable with persistence N_{run} .

$$|RE(t)| > \tau \Rightarrow \text{drift}. \quad (7)$$

4. Experiments

4.1 Data collection

Plant instrumentation data were recorded at 10-min intervals over approximately 55 days during a PWR flexible-operation campaign, including a 100–80–100% load-following maneuver with about 10 days at reduced power. To increase the diversity of the single measured transient, 40 replica series were generated by process-informed augmentation of its temporal and amplitude characteristics in physical units, as shown in Fig. 4. Sliding windows of length ($L=24$) were then extracted and split into training, validation, and test sets at the series level in an 80:10:10 ratio to prevent data leakage.

The validation set was used for early stopping, while the test set evaluated reconstruction on unseen normal operation. For drift-detection testing, bias and drift failures of prescribed magnitudes were separately injected into the clean measured data, and the detection thresholds and SPRT parameters were calibrated using a held-out normal-operation segment excluded from training and augmentation.

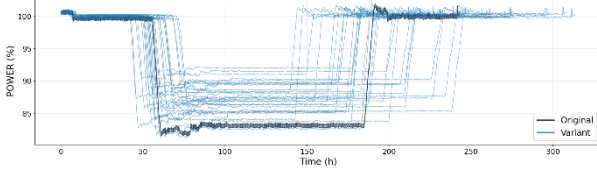


Fig. 4. Training database construction.

For drift-detection evaluation, sensor failures were synthesized from the clean measurement record. As shown in Fig. 5, three failure patterns were considered: bias, forward drift and reverse drift, each at 0.30, 0.45, 0.50, 0.60, 0.75, and 0.90% of instrument span. Each drift type and magnitude was independently injected at step 1,000 into each of the ten variables, yielding 180 test cases that bracketed the calibration tolerance ($\pm 0.25\%$) and the drift criterion ($\pm 0.5\%$ of span). For confusion-matrix scoring, the 0.50% boundary cases were excluded, leaving 150 cases; the 0.30% cases were labeled negative (not alarm), whereas the 0.45–0.90% cases were labeled positive (alarm).

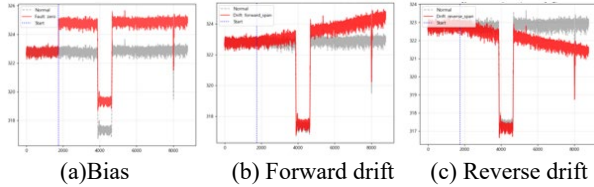


Fig. 5. Types of synthesized sensor failures: (a) bias, (b) forward drift, and (c) reverse drift.

4.2 Input/output variable selection

From the 904 variables available in the plant information system, ten were selected by Pearson correlation analysis: candidate variables were screened by their absolute Pearson correlation with reactor power over the load-following maneuver, and the ten variables with a correlation coefficient of 0.90 or higher ($|r| \geq 0.90$) that remained consistent throughout the maneuver were retained, so that the selected set responds coherently to power changes. The selected variables are listed in Table I. These variables are tightly coupled through the primary–secondary heat balance exactly the redundancy the autoencoder exploits: during a power change all ten variables move along physically consistent trajectories, so a channel departing from the pattern implied by the others is a drift candidate. The input is the normalized 24-step $\times$ 10-variable window. The output is the reconstruction of the same ten variables.

Table I: Selected input/output variables

No.	Variable	Description
1	SG1_PRESS	Steam generator 1 pressure(bar)
2	SG2_PRESS	Steam generator 2 pressure(bar)
3	SG1_STM_TEMP	Steam generator 1 main-steam temperature($^{\circ}\text{C}$)
4	SG2_STM_TEMP	Steam generator 2 main-steam temperature($^{\circ}\text{C}$)
5	HOT_L1	Hot-leg temperature, loop 1($^{\circ}\text{C}$)
6	HOT_L2	Hot-leg temperature, loop 2($^{\circ}\text{C}$)
7	COLD_L1B	Cold-leg temperature, loop 1B($^{\circ}\text{C}$)
8	COLD_L2A	Cold-leg temperature, loop 2A($^{\circ}\text{C}$)
9	COLD_L2B	Cold-leg temperature, loop 2B($^{\circ}\text{C}$)
10	POWER	Reactor power(%)

4.3 Training

The TCN-AE instantiation is shown in Fig. 6: four residual blocks of causal dilated convolutions (kernel 3; dilations 1, 2, 4, 8. 64 channels; batch normalization, GELU, dropout 0.1, skip connections), a 1×1 bottleneck ($64 \rightarrow 32 \rightarrow 64$), and a mirrored decoder with reversed dilations and a 1×1 output projection.

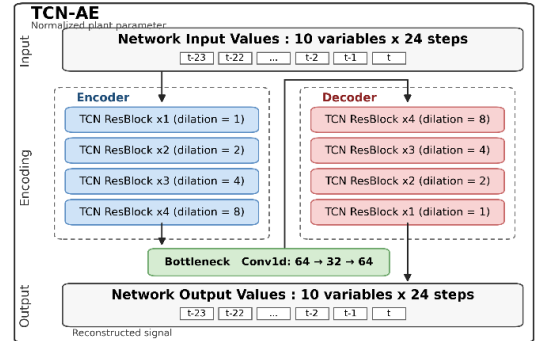


Fig. 6. Schematic Architecture of the TCN-AE.

Training used Adam W (learning rate 1.5×10^{-3} , weight decay 10^{-4}), batch 128, 5-epoch warm-up with cosine decay, mixed precision, gradient clipping, and early stopping (patience 15), converging at epoch 59 with a validation weighted MSE of 4.8×10^{-5} .

5. Results

Fig. 7 shows the TCN-AE SPRT signal validation for the reactor power variable on the normal record: (a) the measured and reconstructed signals agree closely through the load-following transient (shaded); (b) the RE stays within the channel limit ($\pm 0.439\%$ of span); and (c) the SPRT statistics remain far below the alarm limit, producing no alarm.

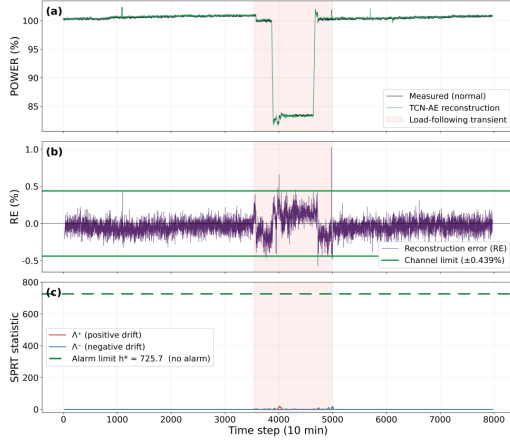


Fig. 7. TCN-AE SPRT Test for reactor power Normal case.

Span-referenced drift cases. Over the 180 span-referenced cases, the channel-matched thresholds with five-step persistence suppressed 0.30%-of-span deviations under steady state as designed, while detection set in from 0.45–0.60% of span depending on channel and delay shrank rapidly with magnitude. Fig. 8 shows a representative case a 0.60%-of-span forward drift on the reactor-power channel: the reconstruction tracks the true process through the maneuver while the drift accumulates in the residual, and the SPRT alarms at $t = 6,728$, about 249 steps (41 h) earlier than the fixed-threshold detection at $t = 6,977$, with no false alarm during the transient.

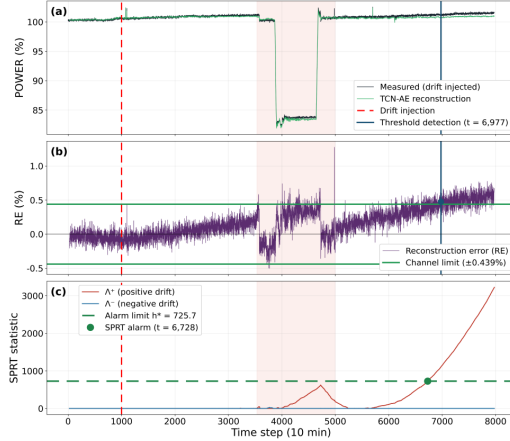


Fig. 8. TCN-AE SPRT Test for reactor power under a 0.60% forward drift.

Finally, the two decision rules were compared over the 150 labeled cases, as summarized in Table II. A single-exceedance fixed threshold is maximally sensitive (95.8% detection) but suffers a 56.7% case-level false-positive rate ($FAR = FP/(FP+TN)$ in Table II), as 0.30% of-span cases occasionally cross the limit on noise spikes. The per-channel SPRT gives up 2.5 percentage points of detection (93.3%) but cuts false alarms more than eight-fold to 6.7%, raising F1 from 0.913 to 0.957. On the clean record under steady state, the SPRT alarmed on only 0.15% of steps (sample-wise false-alarm fraction, a step-level metric distinct from the case-level rate above), versus 4.1% for the fixed threshold. Sequential

accumulation consistently buys false-alarm immunity at a small cost in delay.

Table II: Drift detection performance over the 150 span referenced cases

Metric	Fixed threshold	SPRT
TP	115	112
TN	13	28
FP	17	2
FN	5	8
DR (%)	95.8	93.3
FAR (%)	56.7	6.7
F1	0.913	0.957

6. Conclusion

This study developed a signal-validation framework for NPP flexible operation by combining a TCN-AE reconstruction model with a two-sided SPRT. Trained on an augmented database from a real 100–80–100% load-following record, the framework maintained accurate reconstruction during power maneuvers and detected sub-percent drifts. The per-channel SPRT achieved 93.3% detection with a 6.7% false-alarm rate ($F1 = 0.957$), while the sample-wise false-alarm fraction on clean steady-state data was 0.15%. All three failure types—bias, forward drift, and reverse drift—were successfully detected. Future work will focus on low-SNR channels, reverse drifts in cold-leg signals, and validation using naturally occurring drift data.

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