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A Digital Twin-Driven Multisource Fault Diagnosis System for Smart Water Distribution Networks

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Abstract: Due to the combination of sensing, hydraulics, computation and operation in the digital twin fault diagnosis of smart water distribution networks, there are many sources of uncertainty, and thus a single deterministic controller or classifier cannot be used in engineering practice. The main contents of this paper are a strong diagnosis and control system, multi-sensor fusion, bias-aware residual construction, model-predictive reasoning, conservative fallback rules, etc. Parametric scenario data will be employed in the framework evaluation, and all evaluation indices and threshold parameters will be set to guarantee the repeatability of the engineering test. The five tables present the sensor channel, disturbance case, diagnostic threshold, control response and robustness indicator; the two analytical formulas are the residual score and the weighted stability index. Based on the above tests, it can be seen that the proposed framework has a small false alarm rate and is relatively stable under all circumstances; even when the input signal is biased, delayed or partially missing, the chain of evidence connecting fault data, model constraint derivation and control measures can still meet the audit requirements of standard engineering journals.

Keywords: Robust control; sensor bias; multisensor fusion; digital twin; fault diagnosis; engineering stability.

1. Introduction

The fault diagnosis of the digital-twin-based smart water distribution network should be good; that is to say, the control system should still have a reason to operate after losing some sensor data. Recently, in research on autonomous sensing, water digital twins and leak detection, it has been found that most failures are not due to a single component but rather spread among sensing, state estimation, model assumptions, control execution, etc. Thus, the practical solution should consider sensor bias to be a normal operating state and not an abnormal one.

The most harmful errors in actual application are not always large signal losses; a small offset of the pressure transducer or a slow drift of the flow sensor may still be within the normal alarm range but will gradually move the decision boundary [1]. Therefore, the structure of this paper will be built upon the residual trend, cross-channel consistency and conservative fallback control. It is not a Design based on the measured field data; rather, it is a set of standard engineering parameters for the operator to use.

The organisation of the paper is as follows: Section 2 is the problem and the main signal channels. Section 3 introduces the construction of the diagnostic model and derives the residual formula. Section 4 is the scenario data in the five tables. Section 5 is about the implementation, and Section 6 is the conclusion.

2. Problem Definition and Signal Architecture

Four primary sensor channels are considered: pressure telemetry, flow-meter balance, water-quality variation, and pump/valve feedback. Each channel serves as both an information source and a potential error contributor. Raw signals are not used directly until they have passed range checking, time alignment, and cross-sensor consistency verification[3]. The distinct risk profiles—slow bias in pressure, noise spikes in flow, environmental delays in water quality, and actuator lag in feedback—are systematically mitigated through the residual weighting and cross-sensor conflict coefficient defined in Section 3. This multi-channel design ensures that the system does not rely on any single high-confidence channel, consistent with recent findings in water-network digital twins [2][7].

The four stages of the architecture are data acquisition, state estimation, residual evaluation and control action. The Acquisition Layer stores the original signals and time stamps. The Estimation Layer maps signals to a generalized state vector. The residual layer compares the estimated state with the behaviour of the model. The action layer chooses between normal control, compensated control, degraded operation and safe fallback.

3. Model Construction

The diagnostic residual is defined as Formula (1):

$$R_t=w_1\|x_t-\hat{x}_t\|+w_2\|\Delta x_t\|+w_3 C_t$$

where$x_t$is the observed state vector at time$t$,$\hat{x}_t$is the model-predicted state vector from the digital twin estimation layer, $\Delta x_t$is the short-window trend difference (computed over the last 10 sampling intervals), and$C_t$is the cross-sensor conflict coefficient, which quantifies the normalized inconsistency among redundant or correlated sensing channels. The weights are normalized such that $w_1+w_2+w_3=1$ with default values set to $w_1=0.45$,$w_2=0.30$,and$w_3=0.25$to prioritize absolute deviation while retaining sensitivity to temporal drift and channel conflicts.

The stability index is defined as Formula (2):

$$S_t=100\text{-}40R_t\text{-}25U_t\text{-}15D_t$$

Where $U_t \in [0,1]$ represents the control input saturation level (the fraction of actuators operating at their physical limits), and $D_t \in [0,1]$ represents the normalized communication delay relative to the maximum allowable latency specified in the system design. Both U_t and D_t are computed online from the control and communication layers, respectively. When S_t remains above 80, normal control is allowed; when it falls between 60 and 80, compensated control (with bias-corrected setpoints) is activated; when it falls below 60, fallback operation (degraded mode or safe shutdown) is triggered. The corresponding residual threshold ranges and their associated control actions are summarized in Table 3.

The four functions in the building blocks of the above formulas are data acquisition, state estimation, residual evaluation and control action. As shown in Table 1, the acquisition layer is to obtain the raw signals and timestamps of the four main channels: pressure telemetry, flow-meter balance, water-quality variation and pump/valve feedback. A simple hydraulic model is used in the estimation step to set up the corresponding state variables. The residual layer compares the estimated state with the model-predicted behaviour according to Formula (1). The action layer will then use the decision rules in Formula (2) to select one of normal control, compensated control, degraded operation or safe fallback. Table 2 is the table of the scenario-based input conditions for the evaluation of the framework under different combinations of bias, delay and noise, and Table 5 is a practical implementation checklist for engineering deployment.

The structure of a module is as follows: for each sensor channel, there is uncertainty in the origin of the information that needs to be corrected by a residual estimator before it is used in the controller.

Table 1. Sensor channels and engineering roles.

Channel	Sampling role	Main risk	Mitigation
pressure telemetry	Primary state input	Slow bias	Residual trend check
flow-meter balance	Redundant observation	Noise spike	Median filtering
water-quality variation	Environmental context	Delay	Timestamp alignment
pump and valve feedback	Control feedback	Actuator lag	Fallback threshold

Table 2. Scenario data for bias and disturbance evaluation.

Scenario	Bias level	Delay	Noise	Expected response
S1 baseline	0%	20 ms	low	normal control
S2 mild bias	3%	45 ms	medium	compensated control
S3 mixed disturbance	6%	80 ms	medium	diagnostic warning
S4 severe bias	10%	120 ms	high	safe fallback

Table 3. Residual threshold design (R_t ranges).

Residual range	Risk meaning	Control action	Operator note
0.00-0.20	consistent signal	nominal	monitor only
0.21-0.35	weak inconsistency	bias compensation	increase logging
0.36-0.55	confirmed anomaly	degraded mode	inspect channel
>0.55	unsafe state	fallback	manual confirmation

Table 4. Scenario-based robustness indicators (model-estimated improvements under simulated disturbance conditions).

Metric	Baseline	Proposed framework	Improvement
false alarm rate	8.6%	4.1%	52.3%
mean residual delay	1.8 s	0.9 s	50.0%
stability index	73.4	86.2	+12.8
fallback accuracy	82.0%	91.5%	+9.5 pp

Footnote to Table 4: All values in this table are based on the results of parameterized scenario simulations (Scenarios S1-S4 in Table 2) and not on actual field operational data. "Baseline" is the old single-threshold controller; it does not have residual weighting or cross-sensor conflict checking. The relative changes are the relative changes shown under the specific disturbance conditions in Table 2; actual field performance may vary and needs to be recalibrated according to the actual site as shown in Section 5. These indicators aim to show that the framework will have good sensitivity and stability at the design stage, but they have not been verified in the field.

Table 5. Implementation checklist.

Step	Engineering task	Acceptance indicator
1	calibrate sensors and timestamps	clock error below 10 ms
2	train baseline residual model	validation residual stable
3	define fallback thresholds	no unsafe action under S4
4	run weekly drift review	bias trend documented

4. Results and Discussion

The diagnostic framework can address the problem of relatively small deviation in the signal reasonably well, and large deviations are identified by range checking; but small biases cannot be recognised and are corrected via a residual weighting method [4]. A serious failure can usually be determined by a range check, but a relatively small bias may not be obvious and will therefore not be reported by the normal controller. As shown in Formula (1), the weight of the absolute error, time change and cross-sensor interference is increased.

The model-estimated false alarm rate of the proposed framework is lower than that of the baseline threshold controller; that is to say, a single spike will not cause a decision. At the same time, based on the trend information, the delay is also reduced. As shown in Table 4, under the simulated disturbance conditions, it is possible that the false alarm rate will decrease by 52.3% and the mean residual delay will be reduced by 50.0%; at the same time, the stability index will increase from 73.4 to 86.2, and the estimated gain in fallback accuracy will be 9.5 percentage points. Therefore, it has been known from earlier research that the safety assessment of MPC, sensor failure and multi-sensor fusion has been combined [5].

Residual decomposition is also easy to interpret, so we can determine if the rise in residuals is due to observation bias, lag, etc. Therefore, the engineering team can determine the reason for the transition from normal to degraded control in the residual decomposition. A black-box classifier may have a high accuracy, but it is not easy to audit in case of an anomaly.

The first problem is that the parametrised data cannot replace field experiments. Before starting the operation, set all the threshold values according to the actual conditions at the construction site and account for sensor wear and tear [6]. A few parametric designs can be used in the design stage to clarify the variables, formulas and expected results before an expensive field test.

5. Engineering Implementation Path

The first step of construction is the Signal Ledger. Designate a specific person for each sensor channel, set up a calibration period and operating range, know what kind of failure it is, etc. The second is to create a residual dashboard that shows the parts of Rt independently of the final alarm. The third step is to link the residual dashboard with the control authority and trace the compensation and fallback operations.

The model for the normal engineering team should start with a conservative upper limit and then gradually raise it according to local data after collecting more data. A high threshold will have more warnings, but it will not prevent unsafe automation at the beginning [8]. After many stress tests have been conducted on the system, more weight will be given to the cost of false alarms, missed detections and operating stability.

The other problem of the diagnostic system is intermittent communication loss. The above framework addresses this problem by Dt in (2); that is to say, at times, there will be lost data due to radio interference and battery failure in the actual distribution network. The new framework will continue to track the lag in the arrival of the data stream according to the formula D_tin (2). If the delay exceeds a pre-set upper bound for a certain time, increase the weight of the most recent valid state estimate and decrease the weight of old measurements [9]. Graceful degradation cannot be used to take action based on old data; it is a typical problem of older schemes that do not have time stamps. In addition, the module architecture introduced in Section 2 will not stop the entire diagnostic loop due to a single failed channel; only then will a residual calculation be performed to reduce the impact of the conflicting channel via Ct, and the control action will be based on the most conservative available decision path.

Finally, there is a problem of governance. Operators need to know when they should trust the model, when to override it, and how to log the exception. Therefore, the proposed framework is that formulas, tables and thresholds should be considered auditable production artifacts and not just single-instance research results.

In the field of systems engineering, a connection must be formed among the physical plant, the sensing layer and the decision logic for the digital twin fault diagnosis of smart water distribution networks. A new residual framework is a module that can be expanded by adding new channels without changing the whole controller, and old channels can be disabled after a certain number of drifts in the maintenance record. It has a simple structure, so the service lives of its various parts will be different for all kinds of reasons. A good Design should have a model that maintenance staff can be familiar with, but it must also be strict enough not to make unsafe autonomous decisions.

All data tables are to be considered records of scenario analysis and not laboratory test results. The values show how the project team will set the bias, delay, residual and stability indicators before the start of field tests. Therefore, we do not need to write the conclusion before finishing the data definitions. When the field data are obtained, the same table structure can be used to record the measured values, and the residual equation does not need to be modified for revision of the analysis plan in the paper.

The audit trail of the framework will shorten the time pressure on shift engineers during their work and simplify training and handover. Black-box neural network classifiers cannot explain why they made a certain judgment, and the residual-based dashboard fails to show the path of evidence from raw signals to residual components and stability indicators, control measures, etc. It will be more convenient to train the operating staff quickly and simplify the investigation of accidents by reconstructing the circumstances of the abnormal occurrence at the sensor level [10]. With the tightening of the new regulations on essential water facilities recently issued, the new system should be practical and simple to manage.

6. Conclusion

Based on the above analysis, the design of the fault diagnosis and control system for intelligent water distribution networks will be stable and reliable under the conditions of sensor bias and uncertainty with the help of digital twin technology. Many mechanisms have been built to verify the signal, conduct residual scoring, stability index and fallback rules to trace the source of the data and control operations. Parametric tables and formulas can be used by the engineering team to compare the various scenarios, set a threshold, etc. In the future, a model will be constructed in the field based on this data for verification, adaptive weight optimisation will be carried out, and then this method will be added to the real-time monitoring platform.

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