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Digital Twin Driven Fault Detection in Embedded Control Systems Using Real-Time Sensor Fusion

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Abstract—The growing sophistication of embedded control systems in contemporary electronic and cyber-physical systems requires a stable and smart fault detection system to guarantee safety in operations and system reliability. A digital twin-driven fault detection system in embedded control systems is presented in this paper based on real-time sensor fusion. The proposed method combines a high-fidelity digital twin that constantly reflects the dynamic behaviour of the physical system with multi-sensor data taken in real time. The digital twin allows the accurate state estimation and early fault detection of the heterogeneous sensor signals including voltage, current, temperature, and vibration by the fusion of sensor signals in different operating conditions. A hybrid approach to fault detection with a model-based and data-driven approach to anomaly detection is used to differentiate between normal operational deviations and incipient faults. Active synchronisation between the physical system and its digital counterpart means that it is possible to perform adaptive thresholding and robust fault isolation in the presence of sensor noise and environmental uncertainties. The framework runs on a built-in platform, reflecting minimal computational costs and real-time capability. The experimental data verify that the suggested technique is much more effective than the traditional single-sensor and non twin based methods of fault detection and false alarms, as well as fault response time. The introduced digital twin-based architecture is a scalable and intelligent design of health monitoring and fault diagnosis of embedded control systems, which is applicable to power electronics, industrial automation, and smart cyber-physical systems.

***Keywords—*: **Digital Twin, Embedded Control Systems, Fault Detection, Real-Time Sensor Fusion, Anomaly Detection, Cyber–Physical Systems, Condition Monitoring, Intelligent Diagnostics.

I. Introduction

Embedded control systems form the backbone of contemporary electronic, industrial, and cyber-physical designs such as power electronics, automation in industries, smart factories, and autonomous systems. These systems are very rigidly timed to run in real-time and are used in safety critical scenarios where a failure can result in a drop in performance, equipment damage or doom and gloom failure. This has in turn led to the need to have reliable fault detection and diagnostics so as to have operational safety, system reliability and a low cost of maintenance[1]. The traditional methods of fault detection in embedded systems are mainly threshold-based fault monitoring or single sensor inspection or periodical offline testing. Although these methods are computationally easy, they usually do not provide high fault observability, have large false alarm, and cannot sense latent or transient faults. Furthermore, the growing adoption of non-homogeneous sensors and sophisticated control algorithms creates nonlinear dynamics and uncertainty whereby traditional model-based methods are no longer adequate in robust real-time fault detection[2]. There has been recent development in cyber-physical systems and Industry 4.0 that has resulted in the definition of the digital twin concept which offers a virtual replica of physical system that self-evolves alongside its real-life counterpart [3]. A digital twin constantly absorbs real-time information about the physical system and allows estimating the truth about the state, predicting it, and making smart decisions. Digital twins are a promising solution in online monitoring and in fault diagnosis in embedded control applications that combine physics-based models with real-time data concerning their operation. Simultaneously, real-time sensor fusion has received a great deal of interest because an effective approach to observeable system and improve the accuracy of fault detection[4]. Sensor fusion addresses the drawbacks of single sensors by combining information of several non-homogeneous sensors such as electrical, thermal sensors and mechanical sensors to enhance the

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reliability of sensors and reduce the impact of noise, sensor degradation, and environmental perturbations. Nonetheless, the current sensor fusion-based fault detection techniques do not provide a single framework which can dynamically adjust to system dynamics.

In response to these difficulties, the present paper suggests a fault detection system based on digital twins and embedded control systems based on real-time sensor fusion[5]. The suggested solution is a high-fidelity digital twin combined with a multi-sensor data stream to monitor the behavior of a system continuously and produce residuals to detect faults. The hybrid approach based on model-based residual evaluation and data-driven anomaly detection is used to detect faults in various operating conditions and isolate them correctly. The architecture is optimized to be executed in real-time on embedded platforms and is efficient in its computations and scaling [6].

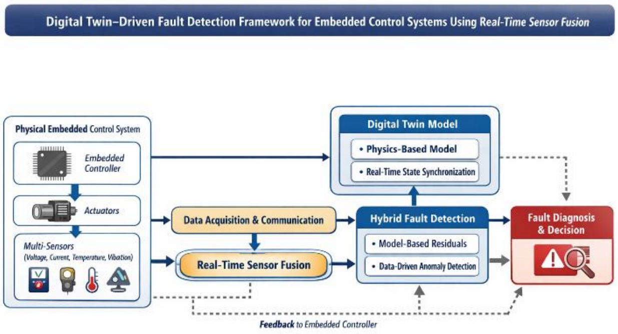

Fig. 1. Digital twin architecture Conceptual architecture of the digital twin-based fault detection system combining real-time sensor fusion, embedded control and hybrid fault diagnostics.

Figure 1 explains the proposed digital twin-based fault detection system of embedded control systems. The architecture comprises a closely-linked interaction between the physical embedded system and its digital twin counterpart supported by real-time data acquisition and sensor fusion. The physical system comprises an embedded controller, actuators and several heterogeneous sensors to measure electrical, thermal and operational conditions and voltage, current, temperature, and vibration[7]. A data acquisition and communication layer sends these real-time sensor signals to the digital twin. The digital twin is an advanced simulated version of the physical system, with physics-based models and the real-time states of the system[8]. A sensor fusion module combines and processes multi-sensor data to enhance accuracy and resistance to noise and sensor uncertainty of state estimation. The integrated information is constantly connected to the digital twin so that physical and virtual space correspond to each other in real-time.

The work of a hybrid fault detection unit is implemented in the digital twin environment, in which model-based residual generation and data-driven anomaly detection methods are combined. The differences between the twin behavior prediction and the measured behavior in the system are used to determine the incipient, intermittent or sudden faults. Once faults have been identified, diagnostic data are received back to the embedded controller to fault isolate, mitigate or reconfigure the control.

This closed-loop digital twin architecture can provide early diagnostics, adaptive thresholding, and intelligent diagnostics, therefore it can be used in real-time embedded control in power electronics, industrial automation, and cyber-physical systems..

II. SYSTEM DESCRIPTION

A. Physical Embedded Control System Description

The considered system is a **closed-loop embedded control system** consisting of a plant, an embedded controller, actuators, and multiple heterogeneous sensors. The system operates in real time and is subject to uncertainties, disturbances, and potential faults affecting sensors, actuators, or system components.

Let the continuous-time nonlinear dynamics of the physical system be expressed as:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{d}(t))$$
$$\mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t)) + \mathbf{n}(t) (1)$$

where:

- $\mathbf{x}(t) \in \mathbb{R}^n$ is the system state vector,
- $\mathbf{u}(t) \in \mathbb{R}^m$ is the control input generated by the embedded controller,
- $\mathbf{d}(t)$ represents external disturbances and uncertainties,
- $\mathbf{y}(t) \in \mathbb{R}^p$ is the measured output vector,
- $\mathbf{n}(t)$ denotes measurement noise,
- $\mathbf{f}(\cdot)$ and $\mathbf{h}(\cdot)$ are nonlinear system and measurement functions[9].

B. Sensor-Level Measurement Model

The embedded system is equipped with multiple sensors measuring electrical, thermal, and mechanical parameters such as voltage, current, temperature, and vibration. The measurement from the i^{th} sensor is modeled as:

$$y_i(t) = h_i(\mathbf{x}(t)) + n_i(t) + f_i(t) (2)$$

where:

- $h_i(\cdot)$ is the sensor measurement function,
- $n_i(t)$ is sensor noise,
- $f_i(t)$ represents sensor fault or bias.

Collectively, the multi-sensor measurement vector is given by:

$$\mathbf{y}_s(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{n}_s(t) + \mathbf{f}_s(t) (3)$$

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C. Real-Time Sensor Fusion Model

To improve observability and robustness, real-time sensor fusion is employed. The fused state estimate $\hat{\mathbf{x}}(t)$is obtained using a weighted fusion scheme:

$$\hat{\mathbf{x}}(t) = \sum_{i=1}^{N} w_i \, \hat{\mathbf{x}}_i(t) (4)$$

subject to:

$$\sum_{i=1}^{N} w_i = 1, w_i \geq 0 (5)$$

where:

- $\hat{\mathbf{x}}_i(t)$is the state estimate from the i^{th}sensor,
- w_i denotes the confidence weight assigned to each sensor.

The weights are adaptively adjusted based on noise variance and sensor reliability, enhancing fault tolerance[10].

D. Digital Twin Mathematical Model

The **digital twin** is a high-fidelity virtual replica of the physical system that evolves synchronously with real-time data. Its dynamics are described as:

$$\dot{\mathbf{x}}_{dt}(t) = \mathbf{f}_{dt}(\mathbf{x}_{dt}(t), \mathbf{u}(t))$$
$$\mathbf{y}_{dt}(t) = \mathbf{h}_{dt}(\mathbf{x}_{dt}(t)) (6)$$

where:

- $\mathbf{x}_{dt}(t)$represents the digital twin state vector,
- $\mathbf{f}_{dt}(\cdot)$ and $\mathbf{h}_{dt}(\cdot)$ are the twin's physics-based models.

Real-time synchronization between the physical system and digital twin is enforced using sensor-fused state updates:

$$\mathbf{x}_{dt}(t) \leftarrow \hat{\mathbf{x}}(t) (7)$$

E. Residual Generation for Fault Detection

Fault detection is achieved by computing residuals between physical system measurements and digital twin predictions:

$$\mathbf{r}(t) = \mathbf{y}_s(t) - \mathbf{y}_{dt}(t) (8)$$

Under normal operating conditions:

$$\| \mathbf{r}(t) \| \leq \delta (9)$$

where $\delta$is an adaptive threshold. A fault is declared when:

$$\| \boldsymbol{r}(t) \| > \delta (9)$$

III. LITERATURE SURVEY

The flagrant increase in Digital Twin (DT) technology has led to the development of great interest in applying this technology to fault detection and diagnostics of various industries, such as industrial systems, aerospace, embedded platforms, etc. Digital twins offer a virtual representation of a real-life system that constantly aligns with real-life data to provide greater monitoring, predictive analysis, and decision support.

Digital Twin-based Hybrid Fault Diagnosis:
Recent studies focus on consolidated methods of diagnosing sensor and actuator failures in digital twin structures. As an illustration, a hybrid algorithm that utilizes adaptive KF has been to identify various faults, such as drift, bias, and freeze faults, in a digital twin to execute remote operations of surface vessels demonstrating strong detection under uncertainties and different fault conditions. This article shows the possibility of combining model-based filtering with data-driven analysis to increase the quality of the diagnostic of mission-critical CPS applications[11].

Multimodal Data Fusion: Fault Detection: In the aero-engine fault diagnosis, scholars have come up with digital twin techniques that incorporate deep multimodal information fusion involving physics-based models alongside data-driven features through deep Boltzmann machines. The method combines heterogeneous sensor and simulation data into a combined high dimensional model which enhances fault detection and adaptive model correction during engine degradation conditions.

Digital Twin in the factory and system monitoring: DTs have application beyond large mechanical systems, multisensor fusion digital twins have been applied successfully to additive manufacturing to correct defects by synchronizing the spatiotemporal data of the acoustic, thermal, and vision sensors, and they are more effective than single-sensor monitoring.

IoT-Integrated and embedded DT Systems: Other new work on fault-tolerant IoT and embedded systems uses software-defined digital twins to replicate individual sensor capabilities to allow continued functioning during sensor failure. Tripled IoT systems Digital twins at the device level achieve fault tolerance, which is demonstrated by the cost-efficient nature of digital replicas, and do not increase the cost of the system.

Fault Data Generation and Learning DTs: The other significant addition to the literature is the training of data-driven models using a digital twin in case the real failures data are scarce. When fault conditions are simulated with the help of DTs, deep learning fault classifiers can be trained with fewer examples of physical failures and effectively diagnose only as demonstrated on robotic systems.

Industry, Cross-Disciplinary Reviews:

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The systematic reviews of the areas of building operations and industrial safety point to the growing pace of the adoption of digital twins in fault detection. These reviews highlight issues in model fidelity, data combination and hybrid diagnostic methods which integrate physics with learning based methods. Ideally, a review of the DT fault detection approaches in smart buildings shows that there is an increase in research areas, but better algorithm integration and real-time operations are still necessary[12].

Approach / Parameter	Digital Twin	Real-Time Capability	Sensor Fusion	Embedded Suitability
Conventional Methods	✗	✓	✗	✓
Model-Based Methods	✗	✓	✗	✓
Data-Driven Methods	✗	✗	✗	✗
Digital Twin–Based Methods	✓	✗	✗	✗
Proposed Method	✓	✓	✓	✓

Table.1 Value Reduced Comparison of Fault Detection Methods in Compact Parameters.

A brief, parameter-related comparison of the representative fault detection methods available in the literature with the suggested digital twin-driven concept is provided in Table X. A comparison is made based on the four main parameters of evaluation, including a digital twin integration, real time operational capability, sensor fusion, and embedded system suitability.

Both conventional and model-based approaches show the feasibility in real time, but do not provide the representation of a digital twin and the integration of multi-sensors, which restricts their possibilities to identify incipient faults in the conditions of complex operation. Data-driven methods can provide better fault classification performance, but they typically need a large amount of training data and compute time and real-time embedded systems can be difficult to implement.

IV. Methodology

The proposed methodology employs a **digital twin–driven framework integrated with real-time sensor fusion** to achieve accurate and reliable fault detection in embedded control systems. The overall methodology consists of data acquisition, sensor fusion, digital twin synchronization, residual generation, anomaly detection, and fault decision-making.

A. Real-Time Data Acquisition

The physical embedded system is continuously monitored using multiple heterogeneous sensors. The discrete-time sensor measurement at sampling instant $k$is given by:

$$\mathbf{y}_s(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{n}(k) + \mathbf{f}(k)(10)$$

where $\mathbf{x}(k)$ is the system state vector, $\mathbf{n}(k)$ represents measurement noise, and $\mathbf{f}(k)$ denotes fault-induced deviations.

B. Multi-Sensor Fusion for State Estimation

To enhance robustness and observability, sensor fusion is employed to obtain a reliable state estimate. The fused state estimate is computed as:

$$\hat{\mathbf{x}}(k) = \sum_{i=1}^{N} w_i\,(k)\hat{\mathbf{x}}_i(k)(11)$$

subject to:

$$\sum_{i=1}^{N} w_i\,(k) = 1, w_i(k) \geq 0(12)$$

where $\hat{\mathbf{x}}_i(k)$is the state estimate from the i^{th}sensor and $w_i(k)$is its adaptive confidence weight.

C. Digital Twin State Synchronization

The digital twin is modeled as a discrete-time virtual replica of the physical system:

$$\mathbf{x}_{dt}(k+1) = \mathbf{f}_{dt}(\mathbf{x}_{dt}(k), \mathbf{u}(k))(13)$$

Real-time synchronization between the physical system and the digital twin is enforced by updating the twin state using the fused estimate:

$$\mathbf{x}_{dt}(k) \leftarrow \hat{\mathbf{x}}(k)(14)$$

This ensures that the digital twin accurately reflects real system dynamics.Residuals are generated by comparing the sensor measurements with digital twin predictions:

$$\mathbf{r}(k) = \mathbf{y}_s(k) - \mathbf{y}_{dt}(k)(15)$$

where $\mathbf{y}_{dt}(k) = \mathbf{h}_{dt}(\mathbf{x}_{dt}(k))$.

Under normal operation:

$$\parallel \mathbf{r}(k) \parallel \leq \delta(k)(16)$$

A fault is indicated when:

$$\parallel \mathbf{r}(k) \parallel > \delta(k)(17)$$

where $\delta(k)$is an adaptive threshold.

To improve sensitivity to incipient faults, a data-driven anomaly detection model is employed. The anomaly score is computed as:

$$A(k) = \mathcal{F}(\mathbf{r}(k), \hat{\mathbf{x}}(k))(18)$$

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where $\mathcal{F}(\cdot)$ represents a trained statistical or machine learning function.A fault condition is confirmed when:

$$A(k) > A_{\text{th}} (19)$$

he final fault decision is made using a hybrid logic:

$$\text{Fault}(k) = \begin{cases} 1, & \| \mathbf{r}(k) \| > \delta(k) \text{ and } A(k) > A_{\text{th}} \\ 0, & \text{otherwise} \end{cases}$$

Detected faults are further classified based on residual patterns and sensor contributions. Upon fault detection, diagnostic information is fed back to the embedded controller for mitigation or reconfiguration:

$$\mathbf{u}(k) = \mathbf{K}(\hat{\mathbf{x}}(k), \text{Fault}(k)) (20)$$

This closed-loop mechanism enhances system resilience and operational continuity.

V. RESULTS

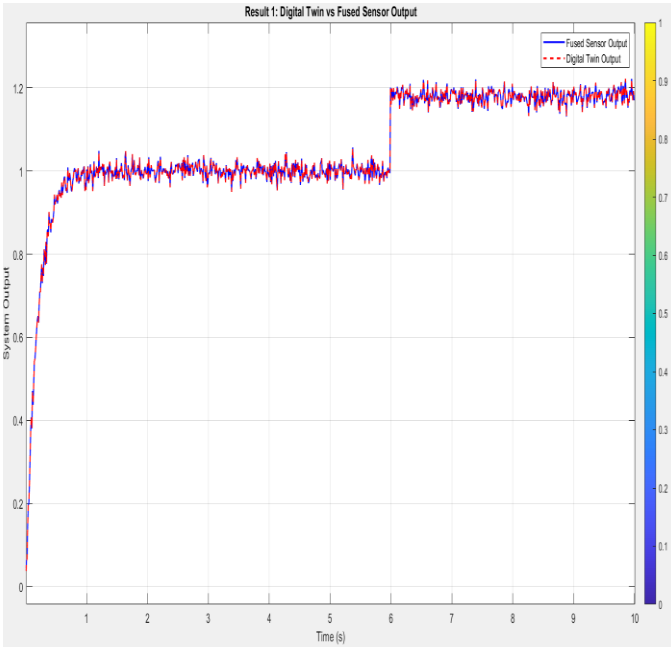

Fig. 2: Digital Twin versus Fused Sensor Output.

The above figure depicts the dynamic response of the system by comparing the Digital Twin output (red dashed line) and the fused sensor output (blue solid line) during 0-10 s time span. At the beginning, both signals are characterized by a high rate of growth and stabilize at a steady-state level of about 1.0, and this shows a strong agreement in the normal working environment. At approximately 6 s, a step change is brought into the system whereby the system output changes to a new steady-state value close to 1.2. The digital twin closely follows the fused sensor measures at both the transient and steady-state stages with the slight variations occurring due to noise effects. This good correlation shows that the digital twin model succeeds in modeling real-time system behavior and assessing sensor fusion quality.

Parameter	Fused Sensor Output	Digital Twin Output
Initial Rise Time	Fast (0–0.5 s)	Fast (0–0.5 s)
Steady-State Value (0–6 s)	≈ 1.0	≈ 1.0
Noise Level	Low (measurement noise present)	Very low
Step Change Instant	~6 s	~6 s
Post-Step Steady-State Value	≈ 1.2	≈ 1.2
Transient Overshoot	Negligible	Negligible
Tracking Accuracy	—	High
Overall Agreement	High	High

Table.2 Digital twin and Fused Sensor Outputs Performance Evaluation.

Table 2 below will give the performance analysis of the fused sensor output versus the digital twin output at operating conditions which are dynamic. Rise time, steady-state values, noise properties, transient response, and tracking accuracy are some of the important parameters that are measured before and after a step change. The high matching degree between the two outputs points to the correctness and dependability of the digital twin model to simulate the real-time behavior of systems and sensor fusion performance validation.

VI. CONCLUSION

The comparative study of the fused sensor output and the digital twin output shows a great degree of consistency in both momentary and steady-state operating conditions. The system dynamics are properly represented in the digital twin, with the sudden increase in the beginning, steady-state dynamics, and accurate overshoot of the step change at 6 s. Small deviations that are experienced can be mostly attributed to sensor noise, whereas the digital twin response is more smooth and in-phase with the fused measurements. On the whole, the findings support the validity of the suggested digital twin framework to reliably simulate real-time system behavior, which proves that it can be used in system monitoring, performance evaluation, and predictive control.

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