

Integrating AI with State Estimation for Fault Detection in Dynamic Systems: Methods, Challenges, and Opportunities

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Abstract

State estimation is a fundamental component of model-based Fault Detection and Diagnosis (FDD) in dynamic systems, underpinning real-time monitoring, predictive maintenance, and safety-critical operations across industries such as aerospace, power systems, robotics, and autonomous vehicles. Traditional estimators, including the Kalman Filter (KF) and its variants, provide physically interpretable residuals for fault detection but often fail to deliver reliable performance under nonlinear dynamics, modeling uncertainties, sensor faults, and non-Gaussian noise. This paper presents a comprehensive review of state estimation-based FDD approaches, with a particular focus on Artificial Intelligence (AI)-augmented Kalman filtering and hybrid frameworks that integrate Machine Learning (ML) models, including Neural Networks (NNs), Support Vector Machines (SVMs), and Gaussian Processes (GPs), with classical estimation theory. The review systematically evaluates model-based, data-driven, and hybrid methods, comparing their robustness, accuracy, computational efficiency, scalability, and interpretability in complex Cyber-Physical Systems (CPSs). Furthermore, emerging trends and open research challenges are identified, including online adaptation, fault-tolerant estimation, sensor fusion, explainable artificial intelligence (XAI), and deployment in Industry 4.0 and Internet of Things (IoT)-enabled environments. By bridging classical estimation theory with modern AI techniques, this review provides a roadmap for designing intelligent, adaptive, and resilient FDD systems capable of enhancing reliability, operational safety, and real-world applicability.

Keywords: state estimation; fault detection and diagnosis; Kalman filter; artificial intelligence; machine learning; hybrid estimation frameworks; cyber-physical systems; sensor fusion; predictive maintenance; explainable AI; Industry 4.0



Received: 6 June 2026
Revised: 24 June 2026
Accepted: 9 July 2026
Published: 13 July 2026

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1. Introduction

In contemporary dynamic systems, state estimation plays a pivotal role in reconstructing system variables that are not directly measurable [1–4]. By integrating mathematical models with sensor data, state estimation provides real-time insights into internal system behavior, enabling precise monitoring, control, and decision-making under uncertainty [5,6]. Its relevance has grown significantly in recent years, evolving from a theoretical concept in control engineering to a cornerstone of advanced industrial applications. This evolution is driven by the increasing complexity of modern systems, the widespread deployment of

Cyber-Physical Systems (CPSs), and the rising demand for predictive maintenance and reliable Fault Detection and Diagnosis (FDD) in Industry 4.0 ecosystems [7–10].

FDD are indispensable for ensuring safety, reliability, and operational efficiency across a wide range of engineering domains, including aerospace, automotive systems, power grids, robotics, and manufacturing [11–14]. Model-based techniques leverage mathematical representations of system dynamics to generate residuals, defined as the difference between predicted and measured outputs, which serve as indicators of abnormal behavior. The effectiveness of residual generation lies in its ability to remain small in fault-free conditions and to exhibit pronounced deviation when faults occur, thereby enabling timely detection of anomalies [15]. However, designing residuals that are simultaneously sensitive to faults and robust to disturbances, noise, and modeling uncertainties remains a significant challenge in classical approaches.

State estimation fundamentally underpins residual generation. Classical estimators such as Kalman Filter (KF) and its nonlinear extensions, Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), have been widely used for state estimation under Gaussian noise and known dynamics [16]. These methods offer strong theoretical guarantees and physical interpretability. However, their performance degrades significantly in the presence of severe nonlinearities, imperfect models, or complex noise distributions [17,18]. For instance, EKF suffers from linearization errors and requires Jacobian computations, while even advanced variants like the Cubature Kalman Filter (CKF) may struggle with model uncertainty and cyber-attack scenarios in complex power systems [19]. Observer-based strategies provide alternative estimation frameworks but typically demand accurate system models and careful parameter tuning, which are often impractical in modern high-dimensional systems [20].

The advent of Artificial Intelligence (AI) and Machine Learning (ML) has opened new avenues for enhancing both state estimation and fault diagnosis [21]. Data-driven AI techniques, including Deep Learning (DL) models, Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and hybrid architectures can learn complex non-linear mappings directly from sensor data and adapt to changing system dynamics without requiring explicit mathematical models [22–24]. Moreover, AI approaches have begun to address critical challenges in predictive maintenance, anomaly detection, and prognostics by integrating temporal and spatial patterns in sensor streams, often leveraging Internet of Things (IoT) data and Digital Twin (DT) technologies for comprehensive monitoring and prediction [25–27]. Recent research also emphasizes the challenges of data imbalance and sensor drift in industrial implementations, highlighting the need for robust AI-enhanced estimation strategies [8].

A particularly important trend is the development of hybrid frameworks that synergistically combine the strengths of classical estimators with AI techniques. These hybrid AI-estimator systems aim to retain the interpretability and structure of model-based methods while exploiting the adaptability and representation power of AI, resulting in improved robustness, accuracy, and fault sensitivity [28]. For example, AI-aided KF fuse Neural Network (NN) modules with Kalman-type algorithms to learn unknown dynamics or noise characteristics, yielding state estimation that adapts to partially known or time-varying models [29,30]. Other hybrid strategies integrate ML with DT models to empower real-time fault diagnosis in complex applications such as electric vehicle motor drives [27,31].

Despite significant advances, several challenges persist. Data availability and quality remain central issues, particularly due to the scarcity of labeled fault data and severe class imbalance inherent in industrial monitoring environments. Explainability and interpretability of AI models also require further research to build trust in safety-critical domains. Furthermore, seamless integration of AI with existing control and monitoring

infrastructures, as well as cybersecurity considerations, remain key barriers to widespread adoption [32,33].

This review presents a comprehensive survey of state estimation-based FDD methods for dynamic systems, focusing on AI-augmented Kalman filtering and hybrid frameworks. Figure 1 clarifies the chronological evolution of the state estimation methodologies for fault diagnosis covered in this paper, transitioning from classical approaches to hybrid AI-Kalman frameworks unified by KF as the common central thread.

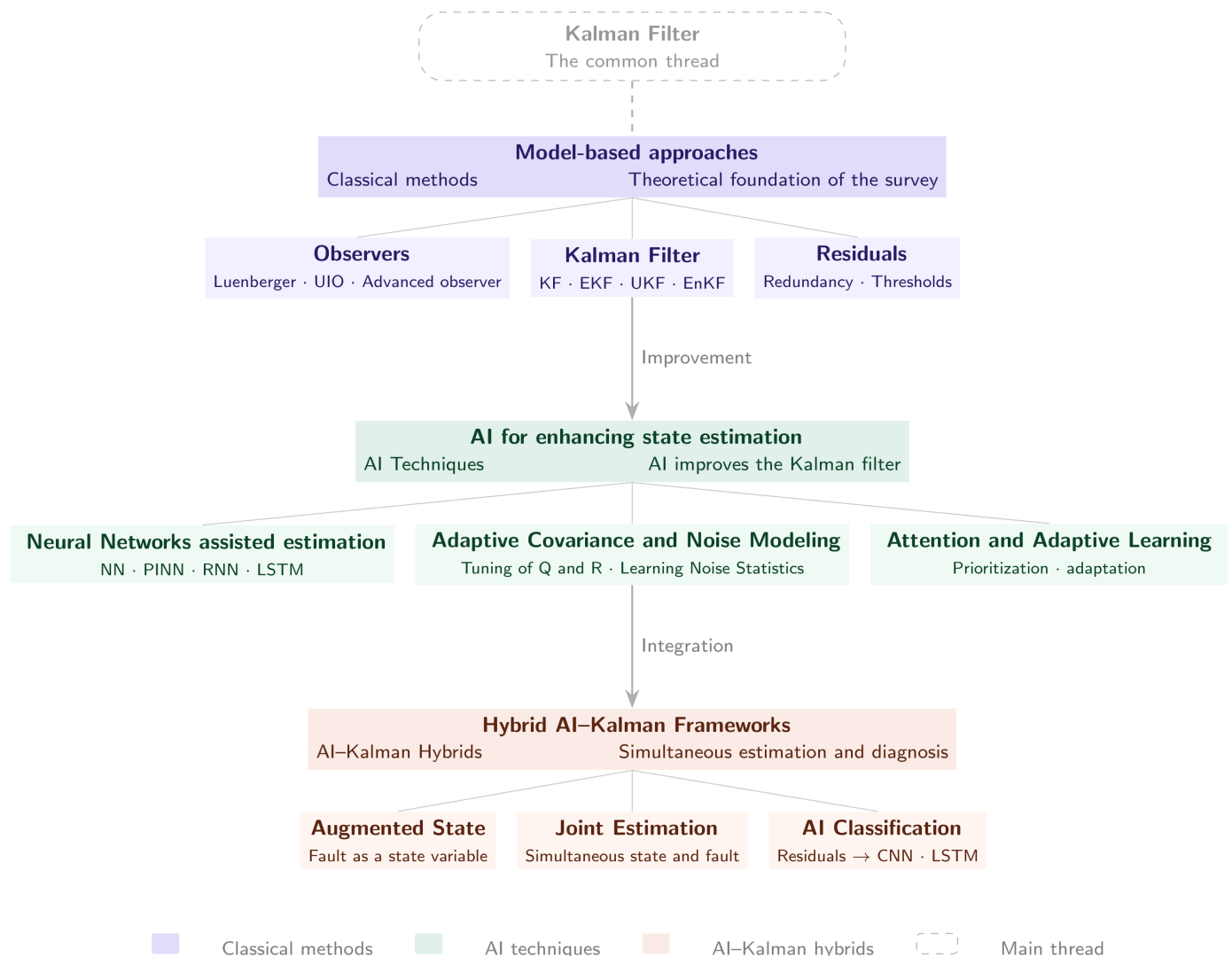


Figure 1. Roadmap of the review structure. The figure illustrates the logical flow from classical model-based fault detection and state estimation, through AI enhancement techniques, to hybrid AI-Kalman frameworks.

Model-based, data-driven, and hybrid methods are critically analyzed, highlighting their strengths, limitations, and real-world applicability. To provide clarity and visual impact, Table 1 summarizes the main characteristics, advantages, and challenges of representative estimation approaches, offering a quick reference for researchers and practitioners.

The remainder of this paper is organized as follows. Section 2 reviews model-based fault detection and state estimation approaches, while Section 3 discusses their inherent limitations. Section 4 introduces AI-based techniques to capture unknown dynamics and improve robustness to modeling uncertainties and noise. Section 5 presents hybrid AI-Kalman frameworks, with a particular focus on joint state and fault estimation. Section 6

provides representative case studies across power systems, industrial processes, robotics and autonomous systems. Section 7 offers a comparative discussion of the reviewed approaches. Section 8 highlights key challenges and outlines future research directions, and finally, Section 9 presents the conclusion of the paper.

Table 1. Comparison of State Estimation Approaches for Fault Detection and Diagnosis in Dynamic Systems.

Approach	Key Techniques	Strengths	Limitations	Representative Use Cases
Classical Kalman Filters [34–38]	KF, EKF, UKF, CKF	Physically interpretable, proven convergence	Sensitive to model uncertainty, limited nonlinear capability	Aerospace navigation, linear process control
Observer-Based [39,40]	Luenberger, Sliding Mode	Low complexity, provable stability	Requires precise models, tuning challenges	Industrial automation, chemical reactors
Data-Driven AI [41,42]	Neural networks, SVM, CNN, LSTM	Handles nonlinearities, adaptive learning	Data hunger, limited interpretability	Smart grids, autonomous systems
Hybrid AI-Estimator [43,44]	AI + KF/UKF, digital twins	Combines structure and flexibility, robust features	Higher computation, integration complexity	Industry 4.0 predictive maintenance, EV motors

2. Model-Based Fault Detection and State Estimation

2.1. Observer-Based Fault Diagnosis

Observer-Based Fault Diagnosis (OBFD) methods provide a mathematically rigorous framework for monitoring the internal states of complex dynamical systems. The central idea of OBFD is analytical redundancy, whereby the system’s mathematical model is used to generate estimates of internal states that can be compared with measured outputs to reveal the presence of faults and disturbances [45,46]. Compared to hardware redundancy, analytical redundancy is cost-effective and scalable, especially in industrial and CPSs where sensor and actuator redundancy is impractical.

The selection of an appropriate observer depends on system properties such as linearity or nonlinearity, the presence of stochastic noise, and robustness requirements against unknown inputs or disturbances.

In this section, we focus primarily on two classical observers widely used in fault diagnosis: Luenberger Observer and the Unknown Input Observer (UIO). These structures form the basis for many advanced estimation designs including robust, sliding mode, and adaptive observers.

2.1.1. Luenberger Observer

Luenberger observer is originally proposed as an effective linear state estimator for systems with known inputs and outputs. The observer reconstructs the system state by combining the nominal model with an output feedback term that corrects the estimate based on the difference between measured and estimated outputs [46,47].

Luenberger observer is expressed as:

$$\hat{x}_{k+1} = A\hat{x}_k + Bu_k + L(y_k - C\hat{x}_k)$$

(1)

Here, $\hat{x}_k$ represents the estimated state vector, u_k is the control input, and y_k is the measured output. The gain matrix L is designed to ensure the convergence of the state estimation error:

$$e_k = x_k - \hat{x}_k \quad (2)$$

whose dynamics are given by:

$$e_{k+1} = (A - LC)e_k. \quad (3)$$

The eigenvalues of $(A - LC)$ are placed inside the unit circle to guarantee asymptotic convergence of the estimation error. The design of L typically relies on standard pole-placement or optimal estimation techniques (e.g., via Linear Matrix Inequalities or Riccati equations).

While Luenberger observer is conceptually simple and computationally efficient, it assumes that all inputs and disturbances affecting the system are known, which limits its effectiveness in the presence of unknown inputs, unmodeled dynamics, or sensor faults.

2.1.2. Unknown Input Observer (UIO)

UIO extends the classical state observer to systems with unknown inputs or disturbances. This kind of observer is designed such that the estimation error dynamics are decoupled from unknown inputs, making it particularly useful for disturbance rejection and fault detection.

Consider a linear system with unknown inputs [48,49]:

$$\begin{cases} x_{k+1} &= Ax_k + Bu_k + Dv_k \\ y_k &= Cx_k \end{cases} \quad (4)$$

where v_k represents unknown inputs or disturbances, and D is the distribution matrix of these unknown influences. A conventional observer cannot ensure convergence of the error since v_k acts as a persistent excitation on the error dynamics.

A UIO structure typically uses a transformation of the state estimate through auxiliary variables:

$$z_{k+1} = Fz_k + TBu_k + Ky_k \quad (5)$$

$$\hat{x}_k = z_k + Hy_k \quad (6)$$

In this structure:

- z_k is a transformed state estimate,
- F defines the observer dynamics,
- T is an input decoupling matrix,
- K is an output injection gain,
- H is an output reconstruction matrix designed for disturbance decoupling.

The estimation error $e_k = x_k - \hat{x}_k$ then follows:

$$e_{k+1} = Fe_k \quad (7)$$

provided the unknown inputs are successfully decoupled. This decoupling requires satisfaction of the following rank condition:

$$\text{rank}(CD) = \text{rank}(D) \quad (8)$$

which implies that D must be structurally observable through C .

Deriving F , T , K , and H involves solving algebraic constraints that ensure the unknown inputs drop out of the error dynamics and that F is a stable matrix. This requirement often makes UIO design more complex than Luenberger observer, but its reward is a robust estimate even in the presence of persistent disturbances or faults.

2.1.3. Comparative Insights and Observations

Both Luenberger observer and UIO share common foundations in state-space modeling, yet they represent fundamentally different strategies for tackling unknown influences. Luenberger observer leverages output feedback to drive the error to zero under the assumption of known inputs, while UIO actively decouples unknown influences from the estimation process. This enhanced capability makes UIOs particularly valuable in fault diagnosis applications.

To further highlight their differences and typical use cases, Table 2 provides a comparative summary.

Table 2. Comparison of Luenberger Observer and Unknown Input Observer (UIO).

Feature	Luenberger Observer [46]	Unknown Input Observer (UIO) [49]
Input Assumption	All system inputs are strictly known	Some inputs are unknown (disturbances, faults)
Mechanism	Minimize error via output feedback gain L	Decouple unknown inputs from estimation error
Design Conditions	Observability only	Observability + rank/decoupling conditions
Complexity	Low (single gain matrix)	Higher (multiple design matrices, algebraic constraints)
Robustness to Disturbances	Limited	High (if decoupling conditions met)
Fault Discrimination	Implicit	Explicit (better isolation of unknown inputs)
Typical Applications	Known-input systems, control	Disturbance rejection, fault detection

2.1.4. Extensions and Advanced Observer Types

Beyond these classical observers, advanced observers such as sliding mode observers, high-gain observers, interval observers, and adaptive observers have been developed to improve robustness against nonlinearities, bounded uncertainties, and time-varying disturbances [50]. Sliding mode observers, for example, exploit discontinuous injection terms to reject matched uncertainties, while adaptive observers adjust gain matrices online based on error trends. These structures can be seen as extensions that build on the foundations established by Luenberger observers and UIOs.

Overall, OBFDD constitutes a foundational layer in model-based estimation and FDD, providing tools that are both theoretically grounded and practically effective when model assumptions are satisfied.

2.2. Kalman Filter and Its Variants

KF and its extended versions are central to model-based state estimation and fault detection in dynamic systems. The classical KF provides an optimal recursive algorithm for linear stochastic systems, integrating system models with noisy measurements to produce minimum-variance estimates of system states. This capability allows the accurate estimation of unmeasured states, which is crucial for control, monitoring, and fault detection. In the context of fault diagnosis, KF generates analytical redundancy in the form of residuals,

representing the discrepancy between estimated and actual outputs, thereby highlighting abnormal system behavior.

To handle nonlinear systems, non-Gaussian noise, and high-dimensional dynamics, several variants have been developed, including the EKF, UKF and Ensemble Kalman Filter (EnKF). These methods extend the applicability of KF-based approaches to a wider range of complex systems such as aerospace, robotics, energy systems, and industrial processes [51,52].

2.2.1. Kalman Filter (KF)

KF operates in a recursive prediction-correction loop:

Prediction Step:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \quad (9)$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \quad (10)$$

Update Step:

$$r_k = y_k - C\hat{x}_{k|k-1} \quad (11)$$

$$S_k = CP_{k|k-1}C^T + R \quad (12)$$

$$K_k = P_{k|k-1}C^TS_k^{-1} \quad (13)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k r_k \quad (14)$$

$$P_{k|k} = (I - K_k C)P_{k|k-1} \quad (15)$$

KF is optimal for linear systems with Gaussian noise and serves as a baseline for more sophisticated variants.

2.2.2. Extended Kalman Filter (EKF)

EKF extends KF to nonlinear systems by linearizing the state and measurement models around the current estimate using Jacobian matrices.

EKF prediction step uses the nonlinear model [45]:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}) \quad (16)$$

The system Jacobian is computed as:

$$A_k = \left. \frac{\partial f}{\partial x} \right|_{\hat{x}_{k-1|k-1}, u_{k-1}} \quad (17)$$

The covariance prediction follows:

$$P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q \quad (18)$$

The correction step linearizes the measurement function. While widely used, the EKF suffers from linearization errors and can diverge for highly nonlinear systems.

2.2.3. Unscented Kalman Filter (UKF)

UKF addresses EKF limitations by employing deterministic sampling (sigma points) to propagate mean and covariance through nonlinear transformations without linearization. This method provides higher-order accuracy and better estimation for strongly nonlinear systems.

The complete UKF procedure is summarized in Algorithm 1.

Algorithm 1 Unscented Kalman Filter (UKF) for Nonlinear State Estimation.

Input: Initial state estimate $\hat{x}_0$, covariance matrix P_0 , process model $f(\cdot)$, measurement model $h(\cdot)$, process noise covariance Q , measurement noise covariance R .

For $k = 1, \dots, N$ **do**

1. Generate sigma points from $\hat{x}_{k-1|k-1}$ and $P_{k-1|k-1}$.
2. Propagate sigma points through the nonlinear process model $f(\cdot)$.
3. Compute the predicted state estimate $\hat{x}_{k|k-1}$.
4. Compute the predicted covariance matrix $P_{k|k-1}$.
5. Transform the propagated sigma points through the measurement model $h(\cdot)$.
6. Compute the predicted measurement $\hat{y}_{k|k-1}$.
7. Compute the innovation covariance matrix S_k .
8. Compute the cross-covariance matrix P_{xy} .
9. Calculate the Kalman gain:

$$K_k = P_{xy} S_k^{-1}.$$

10. Update the state estimate:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (y_k - \hat{y}_{k|k-1}).$$

11. Update the covariance matrix:

$$P_{k|k} = P_{k|k-1} - K_k S_k K_k^T.$$

12. Compute the residual:

$$r_k = y_k - \hat{y}_{k|k-1}.$$

End For

2.2.4. Ensemble Kalman Filter (EnKF)

EnKF is designed for high-dimensional, nonlinear, or stochastic systems, avoiding explicit computation of large covariance matrices. The state is represented by an ensemble of system realizations, propagated through the nonlinear model. Each ensemble member is updated using perturbed measurements [45,53]:

$$x_{k,i}^f = f(x_{k-1,i}^a) + w_{k,i} \quad (19)$$

$$\tilde{x}_k^f = \frac{1}{N} \sum_{i=1}^N x_{k,i}^f \quad (20)$$

$$P_k^f = \frac{1}{N-1} \sum_{i=1}^N (x_{k,i}^f - \tilde{x}_k^f)(x_{k,i}^f - \tilde{x}_k^f)^T \quad (21)$$

$$y_{k,i} = y_k + \epsilon_{k,i}, \quad \epsilon_{k,i} \sim \mathcal{N}(0, R) \quad (22)$$

$$x_{k,i}^a = x_{k,i}^f + K_k (y_{k,i} - H x_{k,i}^f) \quad (23)$$

EnKF is particularly suitable for applications in weather forecasting, oceanography, and other high-dimensional systems [51,52].

2.2.5. Comparative Insights

Table 3 provides a comparative overview of the most widely used state estimation techniques and observers, highlighting their preferred application domains, underlying strengths, and practical limitations. The comparison reveals that no single estimation method can be considered universally optimal; rather, the choice of estimator depends

strongly on the system characteristics, computational resources, modeling accuracy, and performance requirements.

For linear systems with well-characterized Gaussian noise, the KF remains the benchmark solution due to its optimality and computational efficiency. Consequently, it continues to be extensively adopted in industrial process monitoring and control applications. However, the increasing complexity of modern cyber-physical systems has led to the widespread adoption of nonlinear filtering approaches. In mobile robotics, where system dynamics and sensor measurements are inherently nonlinear, the EKF offers a practical compromise between estimation accuracy and computational burden. Nevertheless, its reliance on local linearization may result in degraded performance or even divergence when the nonlinearities become severe.

To overcome the limitations of linearization, the UKF employs deterministic sampling strategies that capture nonlinear transformations more accurately. This characteristic explains its popularity in aerospace guidance, navigation, and attitude estimation problems, where high precision is required. However, the computational complexity of the UKF increases with the state dimension, making its application more challenging for large-scale systems.

For very large-scale and high-dimensional problems, such as weather forecasting and climate prediction, ensemble-based approaches have become the preferred choice. The EnKF significantly reduces computational requirements by propagating an ensemble of state realizations instead of full covariance matrices. This scalability makes it suitable for systems with thousands or even millions of state variables. However, the quality of the estimation depends strongly on the ensemble size, and insufficient ensemble members may introduce sampling errors and filter degradation.

The comparison also highlights the continuing relevance of observer-based approaches in industrial applications. The Luenberger Observer remains attractive for embedded control platforms due to its simplicity, low memory requirements, and ease of implementation. These characteristics are particularly valuable in real-time applications with limited computational resources. Nevertheless, its effectiveness relies heavily on the availability of an accurate linear model, which may not always be achievable in practice.

Similarly, the UIO occupies a unique position among state estimation techniques because of its ability to decouple disturbances and unknown inputs from the estimation process. This feature makes it especially useful for fault detection, fault isolation, and disturbance rejection applications. Despite these advantages, the strict structural and rank conditions required for UIO design often limit its applicability to specific classes of systems.

In summary, the results summarized in Table 3 indicate a clear trend toward selecting estimation methods according to the balance between model complexity, estimation accuracy, computational burden, and robustness requirements. Classical KF-based methods remain dominant in many engineering applications, while advanced variants such as UKF and EnKF address the challenges posed by highly nonlinear and large-scale systems. Observer-based methods continue to offer attractive alternatives when computational efficiency, fault diagnosis capability, or implementation simplicity are primary concerns. Therefore, the selection of an appropriate state estimation technique should be guided not only by theoretical performance but also by practical deployment constraints and application-specific requirements.

Table 3. Typical domains of application for state estimation methods and observers.

Domain Type	Suitable Method	Reason	Limitations
Linear industrial process [34,54]	KF	Optimal linear estimator	Fails on nonlinear system and assumes gaussian noise
Mobile robotics [55–57]	EKF	Practical nonlinear solution	Diverges on strongly nonlinear system
Aerospace attitude control [58,59]	UKF	Higher nonlinear accuracy	Scales poorly to very high dimensions
Weather and climate modeling [60,61]	EnKF	High-dimensional scalability	Sampling error if small ensembles
Embedded control hardware [40,62]	Luenberger Observer	Low computational cost	Requires exact linear model
Fault isolation and disturbance rejection [63]	UIO	Disturbance decoupling	Strict rank condition

2.3. Residual Generation and Evaluation

Residual generation is the process of creating fault-sensitive signals from the difference between model predictions and actual measurements. The design of effective residuals requires careful consideration of fault sensitivity, disturbance robustness, and computational efficiency [64].

At the core of model-based fault detection lies the concept of analytical redundancy. In most physical system, not all internal states can be directly observed. Sensor data provide only partial and noise-corrupted observations, while essential internal variables remain hidden. However, if the system is well-understood its physics, dynamics, and governing equations one can predict its expected behavior. Model-based fault detection leverages this predictive capability by comparing observed outputs with model-based estimates [65].

Analytical redundancy represents a form of knowledge-based verification. In dynamic systems, variables are interconnected through deterministic relationships dictated by physical laws and system dynamics. These relationships ensure that information about the system can be obtained either directly through measurements or indirectly via model computations. This duplication of information redundancy derived from understanding rather than additional sensors forms the foundation of fault detection.

The operational manifestation of analytical redundancy is the residual, defined as the difference between observed and predicted system behavior. Residuals quantify deviations from expected dynamics and provide a measurable signal indicative of faults. When the system operates normally, residuals remain small, reflecting coherence between measurements and model predictions. When faults occur, this coherence is disrupted, resulting in residuals that exceed typical variations. The challenge in residual design is to ensure that they are sensitive to faults while remaining robust to noise, disturbances, and model uncertainties. A well-designed residual distinguishes meaningful deviations from harmless fluctuations, enabling reliable assessment of system health.

In practice, residual evaluation requires thresholding strategies to decide when a deviation is significant enough to indicate a fault. Fixed thresholds often fail to account for variability in noise, disturbances, or modeling errors. Therefore, statistical and adaptive thresholds are widely employed [66].

Statistical thresholds model residuals as stochastic variables, recognizing that even under normal operation, residuals exhibit random fluctuations due to noise and uncertainty. Typically, residuals are assumed to follow a zero-mean Gaussian distribution :

$$r(k) \sim \mathcal{N}(0, S), \quad (24)$$

where S is the residual covariance matrix. A common fault detection rule evaluates the normalized residual magnitude [67]:

$$J(k) = r^T(k) S^{-1} r(k), \quad (25)$$

and declares a fault when

$$J(k) > \gamma, \quad (26)$$

with γ chosen according to a desired confidence level. In this framework, large deviations correspond to statistically unlikely events, signaling inconsistencies between measurements and model predictions .

Adaptive thresholds extend this concept by allowing the decision boundary to vary with operating conditions, system uncertainty, or estimation accuracy [68]:

$$\|r(k)\| > \gamma(k), \quad (27)$$

where $\gamma(k)$ is time-varying.

When system uncertainty increases due to disturbances or modeling errors, the threshold expands to avoid false alarms. Conversely, under more predictable operating conditions, the threshold contracts, enhancing sensitivity to small deviations. This dynamic adjustment provides a more flexible definition of normal behavior, improving the robustness and reliability of fault detection in practical applications.

Together, analytical redundancy, residual generation, and adaptive evaluation form a cohesive methodology for monitoring complex systems. By transforming knowledge of system dynamics into observable signals and decision criteria, these techniques enable accurate, robust, and context-aware fault detection across a wide range of engineered systems.

3. Limitations of Classical Estimation-Based FDD

Classical estimation-based FDD methods, such as KFs and linear observers, have been widely used due to their ability to provide optimal state estimates and residual-based fault monitoring under the assumptions of linear system dynamics and Gaussian noise [34]. By analyzing residuals and their statistical properties, these methods facilitate real-time detection of deviations indicative of faults. However, real-world systems often violate these ideal assumptions, exposing several fundamental limitations that compromise detection performance.

3.1. Nonlinear Dynamics

Many practical systems exhibit strong nonlinearities that challenge classical estimation methods. EKF and similar nonlinear observers attempt to address nonlinearity through local linearization, typically using a first-order Taylor series expansion around the current state estimate [69]. While this approach works near nominal operating points, large deviations or highly nonlinear behavior introduce significant linearization errors. These errors manifest as systematic biases in both state estimates and residuals. Since residual-based FDD assumes nominal residuals to be zero-mean white noise, any bias reduces the sensitivity to genuine faults. In extreme cases, this bias can trigger false alarms during normal transients or mask early-stage faults by shifting residuals away from detection thresholds.

Moreover, classical filters rely on the assumption that posterior state distributions remain approximately Gaussian. In practice, nonlinear dynamics often generate non-Gaussian, multimodal, or skewed distributions that a single mean and covariance cannot capture accurately. This mismatch affects the convergence of estimators, leading to residuals that no longer reliably reflect the probability of measurements [70–74]. As a result, classical tests such as chi-squared or whiteness checks become unreliable, degrading fault detection and isolation performance [75].

3.2. Modeling Uncertainties

Another core limitation stems from modeling uncertainties. Classical FDD relies on fixed nominal models, and any mismatch between the model and the true system can produce structured residuals resembling fault signatures [76]. This creates a fundamental trade-off: setting thresholds high to avoid false alarms reduces sensitivity to small, incipient faults, while low thresholds increase false alarms.

Parametric uncertainties, unmodeled high-frequency dynamics, or neglected nonlinearities can significantly degrade the convergence and accuracy of classical observers. Observer-based systems can also suffer from a “feedback effect,” where the estimated states suppress subtle fault signals. In closed-loop configurations, controllers may inadvertently mask degradation, further complicating detection. Consequently, faults smaller than residual deviations caused by model mismatch may remain undetected, limiting the reliability of classical FDD approaches.

3.3. Non-Gaussian Noise

Classical FDD frameworks assume Gaussian process and measurement noise. Violations of this assumption directly impact residual statistics and threshold-based detection, reducing reliability [77,78]. Non-Gaussian disturbances such as heavy-tailed, impulsive, or correlated noise can create several challenges:

- **Reduced fault detectability:** Fault signatures embedded in heavy-tailed or impulsive noise are difficult to distinguish from noise excursions, lowering true positive rates [79].
- **Increased false alarms:** Large noise spikes can cause residuals to exceed thresholds, leading to more frequent false alarms [80,81].
- **Threshold miscalibration:** Statistical thresholds based on Gaussian assumptions no longer correspond to actual false alarm probabilities [82].
- **Suboptimal residual tests:** Kalman-based residual tests optimized for Gaussian noise lose their optimality, degrading detection performance [83].

3.4. Sensitivity to Parameter Variations

Estimation-based FDD methods are usually tuned to a specific nominal parameter set. Over time, physical systems experience parameter drifts due to component aging, wear, or gradual degradation, which shift system dynamics from their nominal behavior [84]. In fixed-model frameworks, such shifts are interpreted as faults, causing false alarms and reducing the trustworthiness of detection results.

3.5. Interacting Limitations

These limitations often interact and amplify one another. For instance, linearization errors in nonlinear systems are compounded by modeling uncertainties, making observers less stable and less sensitive to faults. Similarly, non-Gaussian noise can obscure the statistical signature of residuals, making it harder to distinguish between modeling errors and genuine faults. Such interactions highlight the need for advanced estimation and

residual evaluation strategies capable of addressing nonlinearities, uncertainties, and non-Gaussian disturbances simultaneously. Table 4 summarizes the key limitations affecting the performance of classical model-based FDD approaches.

Table 4. Key limitations affecting classical model-based FDD performance.

Limitation Category	Primary Failure Mode	Impact on FDD Performance
Nonlinear Dynamics [85]	Linearization error (Taylor expansion bias)	Systematic bias in residuals; reduced sensitivity to small faults
Modeling Uncertainties [76,86]	Masking of faults due to model mismatch	High false-alarm rate or missed detections
Non-Gaussian Noise [87]	Violation of Gaussian assumptions	Unreliable statistical thresholds; failure of second-moment tests
Parameter Variations [65]	Sensitivity to drifts/aging	False alarms due to system degradation

4. AI Techniques for Enhancing State Estimation

The performance of classical estimation-based FDD approaches is fundamentally limited by the assumption that the system model accurately captures nominal behavior. Additionally, these approaches rely on assumptions such as Gaussian process and measurement noise with known stationary covariance, and that all measurements contribute equally to state reconstruction.

In practice, real systems often violate these assumptions. They can exhibit strong nonlinearities, non-Gaussian noise, and continuously evolving operating conditions. Consequently, classical estimation-based FDD methods may fail to provide accurate state estimates, which directly undermines the robustness and reliability of fault detection mechanisms.

To overcome these challenges, recent research increasingly integrates AI techniques into the state estimation process. AI-assisted estimation complements, rather than replaces, classical models by learning residual dynamics, compensating for modeling errors, and improving adaptability to complex operating conditions. This section reviews the main approaches [30].

4.1. Neural Network-Assisted Estimation

Neural network-assisted state estimation is built on the premise that the physical model captures the core system behavior, while a neural network learns and corrects unmodeled or uncertain dynamics from data. This hybrid approach enhances the accuracy of state estimation and strengthens fault detection.

- **Learning Unknown Dynamics:** Classical filters assume the system model is fully known, but in many practical scenarios, incomplete knowledge introduces estimation errors. NNs can learn unknown dynamics directly from data, capturing nonlinearities and complex interactions that classical models overlook.

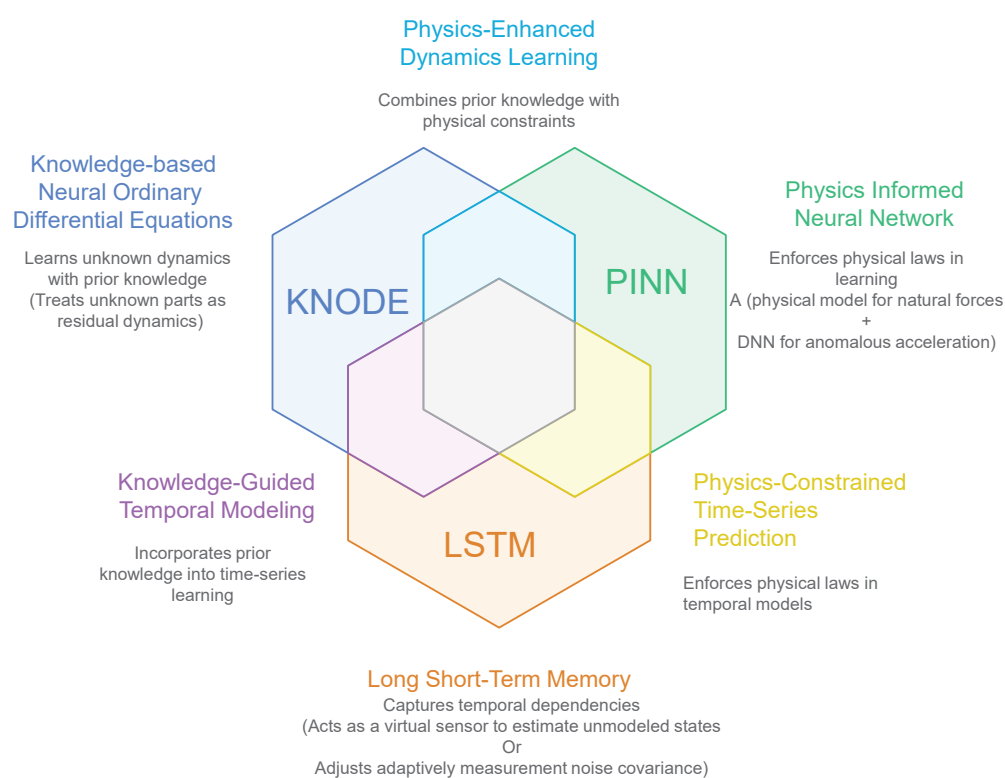
Table 5 summarizes some representative NN approaches for learning unknown dynamics across various domains.

Table 5. Neural Networks for Learning Unknown System Dynamics.

Reference	Technique	Domain	Enhancement
[88]	KNODE (Knowledge-based Neural ODEs)	Quadrotor and ground vehicles	Improved estimation accuracy
[89]	PINN (Physics-Informed Neural Networks)	Satellite state estimation	Enhanced position propagation accuracy
[90]	LSTM (Long Short-Term Memory)	Vehicle dynamics (longitudinal velocity, sideslip angle)	Higher estimation accuracy

Figure 2 illustrates the integration of NNs Techniques for learning unknown system dynamics.

Neural Network-Assisted Estimation for Learning Unknown Dynamics

**Figure 2.** Neural Networks for Learning Unknown Dynamics.

- **Compensation of Modeling Errors:** Residual mismatches between predicted and actual system behavior are often indicative of modeling errors. AI-based approaches can dynamically detect and compensate for these discrepancies.

For example, the Split KalmanNet framework learns the difference between the real system and its mathematical model, inserting a neural correction within the Kalman filtering process [91–93]. Figure 3 illustrates the flowchart of this approach.

Similarly, neural augmentation techniques use NNs as a compensator block, that corrects errors the classical filters can not explicitly model [94,95]. This hybrid architecture allows the estimator to adaptively improve accuracy while retaining interpretability. Figure 4 shows a typical neural augmentation framework.

- **RNN-Aided Estimation:** RNNs can learn temporal patterns in measurement and residual data, enabling dynamic correction of classical estimators. By capturing system memory effects and sequential dependencies, RNN-aided estimation improves both accuracy and robustness under complex, time-varying conditions [96].

Figure 5 illustrates the workflow of RNN-aided state estimation, showing how temporal patterns in residuals are leveraged to enhance classical filtering.

By integrating AI models with classical filters, these hybrid techniques bridge the gap between physically interpretable estimation and data-driven adaptability. Neural augmentation and RNN-based corrections enable estimators to cope with strong nonlinearities, non-Gaussian noise, and evolving operating conditions, providing more reliable residuals for FDD applications across aerospace, robotics, power systems, and autonomous vehicles.

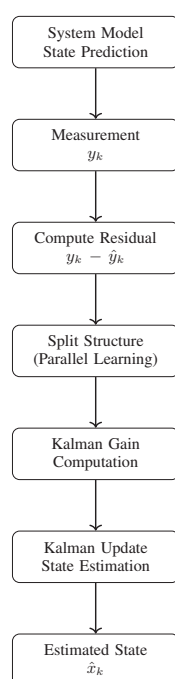


Figure 3. Flowchart of the Split KalmanNet showing neural compensation of modeling errors integrated into the Kalman estimation process.

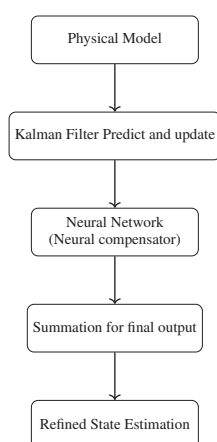


Figure 4. Neural augmentation flowchart illustrating integration of model correction into classical filtering.

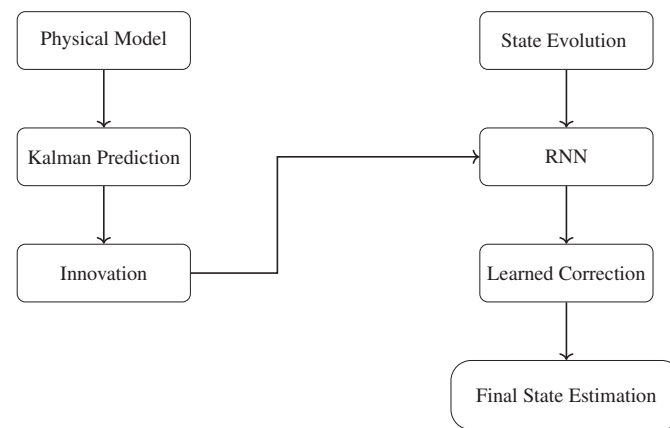


Figure 5. RNN-aided flowchart for adaptive correction of classical state estimators.

4.2. Adaptive Covariance and Noise Modeling

Classical filters assume fixed process and measurement noise covariance matrices, which often leads to inaccurate state estimation and unreliable residuals. In real-world systems, noise statistics are rarely stationary, often unknown, and can exhibit non-Gaussian or time-varying characteristics. AI-based methods provide a powerful avenue to learn and adapt these parameters from data, improving both estimation accuracy and fault detection reliability.

- **AI-Based Covariance Tuning:** AI techniques can dynamically tune the process (Q) and measurement (R) noise covariance matrices to maintain near-optimal filtering performance under changing environmental and operational conditions.

CNNs can analyze structured residuals or sensor measurements to estimate adaptive covariance matrices [97,98], while LSTMs learn temporal relationships between residual patterns and optimal noise statistics.

Despite these advantages, CNNs may be limited by their receptive field, and LSTMs can struggle with very long-term dependencies. The Transformer and Residual Denoising Autoencoder (RDAE) addresses these limitations by incorporating attention mechanisms, which dynamically weigh historical observations based on their relevance to the current state. This enables real-time estimation of the R matrix while capturing long-range dependencies effectively [99].

- **Learning Noise Statistics:** Beyond tuning Q and R , learning the full noise statistics allows the estimator to capture the true structure of uncertainties, including biases, outliers, and nonlinear correlations. This provides a deeper enhancement to state estimation, particularly in complex, uncertain environments.

For example, ProcessNet [100] is an end-to-end deep learning framework designed to adaptively estimate the process noise covariance Q in real time for nonlinear estimators such as the UKF. ProcessNet employs CNN-based subnetworks to process raw accelerometer and gyroscope data, extracting temporal features that are mapped directly to the estimated noise parameters. The predicted values are constrained to remain positive and physically plausible, ensuring filter stability. By updating Q_{k+1} at each time step, the Adaptive Neural UKF (ANUKF) framework maintains optimal confidence between model predictions and incoming measurements, demonstrating substantial improvements in robustness and estimation accuracy, especially under sensor degradation or outages.

Another approach [101] employs a Generative Adversarial Network (GAN) to learn and adapt noise statistics in real time. A lightweight feed-forward Generator predicts

diagonal elements of Q and R based on past UKF performance metrics, while the Discriminator evaluates their realism by comparing predicted versus actual errors. This adversarial feedback loop continuously aligns the filter assumptions with evolving system dynamics, eliminating the need for heuristic tuning.

While both neural network-assisted estimation and adaptive covariance/noise modeling seek to enhance state estimation performance under uncertainty, they fundamentally differ in their underlying philosophies, implementation requirements, and operational characteristics. Neural network-assisted estimation leverages data-driven learning to capture complex nonlinear dynamics, unmodeled behaviors, and unknown system characteristics that are difficult to represent using conventional physics-based models. By learning latent relationships directly from data, neural networks can significantly improve estimation accuracy in highly nonlinear and dynamic environments. However, these benefits are achieved at the cost of substantial training efforts, the need for large and representative datasets, and increased computational requirements during both training and deployment. Furthermore, the performance of neural-network-based estimators may degrade when operating outside the conditions represented in the training data, raising concerns regarding generalization, robustness, and reliability in safety-critical applications.

In contrast, adaptive covariance methods preserve the structure and theoretical foundations of classical Kalman filtering while enhancing robustness through online adjustment of process and measurement noise statistics. Rather than learning the system dynamics themselves, these methods continuously adapt uncertainty representations to reflect changing operating conditions and environmental disturbances. As a result, adaptive covariance techniques generally require minimal prior data, exhibit lower computational complexity, and maintain the transparency and interpretability associated with probabilistic state estimation frameworks. These characteristics make them particularly attractive for real-time embedded systems and industrial applications where computational resources and data availability may be limited.

The comparison presented in Table 6 highlights a fundamental trade-off between flexibility and practicality. Neural network-assisted approaches offer superior modeling capabilities for highly nonlinear systems with significant modeling uncertainty, whereas adaptive covariance methods provide a computationally efficient and interpretable solution for systems where the primary challenge lies in accurately characterizing time-varying uncertainties rather than the dynamics themselves. Consequently, the selection of an appropriate strategy depends on several factors, including the availability and quality of training data, computational constraints, real-time implementation requirements, safety and explainability considerations, and the nature of the uncertainties affecting the system.

Table 6. Comparative overview of NN-aided estimation and Adaptive covariance methods.

Criterion	NN-Aided Estimation [89,90]	Adaptive Covariance [100,101]
Methodology	Learned unknown dynamics and modeling error via neural networks	Online adjustment of process/measurement noise statistics
Computational Complexity	High	Low to moderate
Data Requirement	Large labeled dataset needed	Minimal; adapts online from observations
Interpretability	Moderate (NN embedded within Kalman filter structure; probabilistic framework partially preserved)	High (probabilistic, filter-native)
Best Suited For	Complex, non-linear environments	Uncertain environments

An emerging trend in recent research is the development of hybrid estimation frameworks that combine the strengths of both approaches. In such architectures, neural networks are employed to learn unknown dynamics, model residuals, or estimate uncertainty characteristics, while adaptive filtering mechanisms maintain probabilistic consistency and robustness. These hybrid solutions aim to achieve the high estimation accuracy of data-driven models while preserving the stability, interpretability, and reliability of classical filtering techniques. As artificial intelligence continues to integrate with state estimation theory, such hybrid methods are expected to play an increasingly important role in autonomous systems, intelligent manufacturing, robotics, transportation, and digital twin applications.

4.3. Attention and Adaptive Learning Mechanisms

Attention mechanisms have recently been applied to state estimation to dynamically prioritize the most informative sensor features while adapting to changing operating conditions and system configurations.

- **Feature Prioritization:** Sensor measurements often vary in reliability over time, and not all features contribute equally to accurate state estimation. Attention mechanisms allow neural networks to selectively focus on the most relevant inputs, assigning adaptive weights to features, capturing dependencies among them, or learning multiple relevance patterns simultaneously. This selective prioritization enhances robustness and improves estimation accuracy [102].

Figure 6 illustrates the feature prioritization process in a state estimation framework.

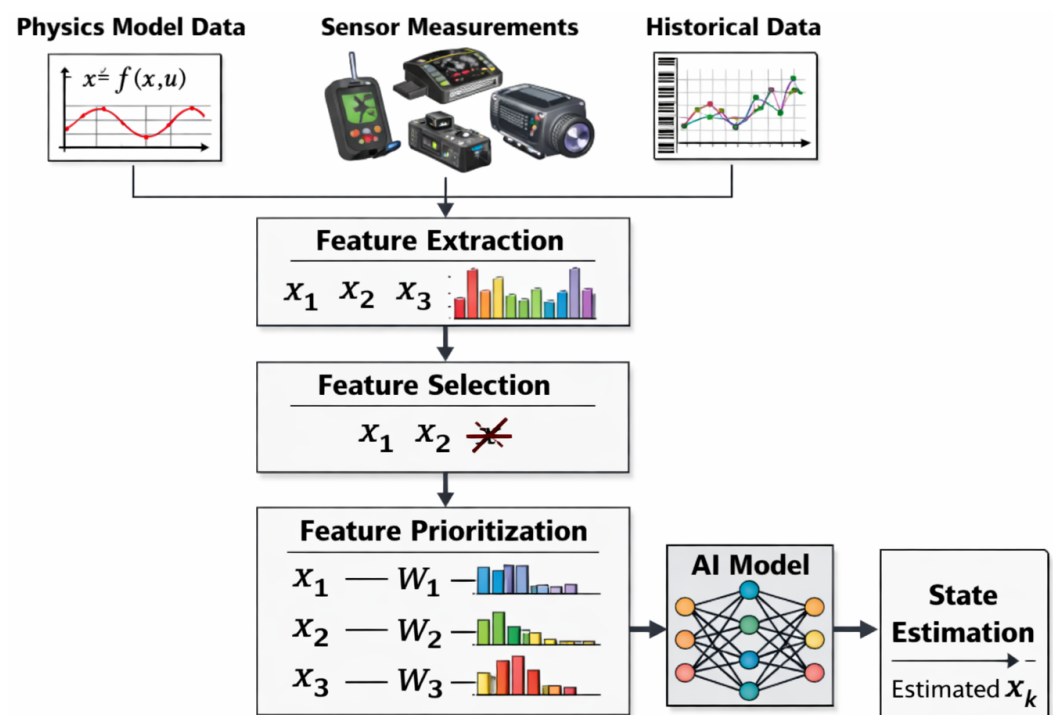


Figure 6. Feature prioritization mechanism for state estimation enhancement using attention networks.

- **Online Adaptation:** Feature relevance is dynamic in real-world systems due to time-varying dynamics, noise statistics, and sensor reliability. A fixed attention model may quickly become suboptimal as conditions evolve. Online adaptation continuously refines attention weights and model parameters using incoming data and real-time estimation feedback. This closed-loop learning mechanism ensures that the estima-

tor remains robust, prioritizing informative measurements while down-weighting unreliable inputs [103].

By combining attention mechanisms with adaptive learning, the system can dynamically adjust both the relative importance of sensor inputs and the associated noise modeling, providing a highly resilient and accurate state estimation framework under challenging, time-varying conditions [102].

4.4. Methodological Quality of Reviewed Studies

To ensure transparency in the literature selection process, the studies included in this survey were identified through a structured screening procedure based on predefined inclusion criteria. Specifically, papers were retained if they were directly relevant to AI-enhanced state estimation methods, published in peer-reviewed journals or conference proceedings, represented recent advances in the field (2020–2026), and demonstrated a meaningful integration of artificial intelligence techniques with classical estimation frameworks. Although no formal quality assessment rubric was employed, priority was given to studies providing sufficient methodological detail, clear experimental protocols, and quantitative performance evaluations that enabled meaningful comparison across approaches.

Following this screening process, a critical examination of the reviewed literature reveals several methodological observations that should be considered when interpreting the reported results. First, no explicit evidence of data leakage was identified in the surveyed studies. Most contributions employ causal estimation architectures in which state estimates are generated exclusively from past and present measurements, thereby avoiding the use of future information. Furthermore, the majority of the reviewed works adopt appropriate training and testing strategies, including temporal data partitioning, independently collected test datasets, cross-validation procedures, or Monte Carlo simulations with distinct random realizations.

Nevertheless, several limitations emerge from the current body of literature. A substantial proportion of the reported studies rely on simulation-based environments, synthetic datasets, or controlled laboratory experiments. While such settings are widely accepted in the state estimation and signal processing communities due to the difficulty of obtaining reliable ground-truth measurements in real-world systems, they inevitably simplify many practical challenges, including sensor degradation, environmental variability, communication delays, model mismatch, and unexpected disturbances. Consequently, the reported improvements in metrics such as root-mean-square error (RMSE), estimation accuracy, fault detection rate, and navigation performance should often be interpreted as achievable under favorable operating conditions rather than guaranteed performance in real-world deployments.

Another important observation concerns the lack of standardized benchmarking protocols. Different studies frequently employ distinct datasets, simulation scenarios, noise assumptions, and performance metrics, making direct quantitative comparison difficult. As a result, many reported improvements should be viewed as demonstrating the potential of a given approach rather than providing definitive evidence of superiority over alternative methods. Future research would benefit significantly from the establishment of common benchmark datasets and evaluation frameworks that facilitate fair and reproducible comparisons.

The survey also highlights a growing gap between estimation accuracy and explainability. While deep learning and hybrid AI-based estimators often achieve superior performance, many studies provide limited insight into the internal decision-making mechanisms of the learned models. This issue is particularly relevant in safety-critical domains such as aerospace, autonomous transportation, industrial process monitoring, and health-

care systems, where transparency and reliability are essential requirements alongside estimation accuracy.

Studies that incorporate independent real-world validation datasets provide stronger evidence of practical generalization and robustness. Notable examples include [99], which evaluates the proposed approach using two independently collected road-test datasets, and [101], which validates its methodology using real aircraft navigation data. Such contributions are particularly valuable because they help bridge the gap between controlled laboratory evaluations and real-world operational environments, thereby increasing confidence in the practical applicability of the proposed methods.

In general, the methodological quality of the reviewed studies is satisfactory and reflects the rapid advancement of AI-enhanced state estimation research. Nevertheless, several challenges remain. Future research would benefit from greater emphasis on real-world validation, reproducibility, standardized benchmarking protocols, uncertainty quantification, and explainable AI techniques. Addressing these issues will be crucial for ensuring that advanced estimation algorithms can be deployed reliably and safely in industrial, transportation, aerospace, and other autonomous-system applications.

5. Hybrid AI-Kalman Frameworks for Fault Diagnosis

Hybrid AI-Kalman frameworks have emerged as a powerful solution for fault diagnosis, combining the physical consistency of model-based estimators with the adaptive learning capabilities of artificial intelligence. These frameworks overcome the limitations of classical estimation methods when faced with model uncertainties, nonlinear dynamics, non-Gaussian noise, and time-varying faults [104]. Figure 7 compares Classical, AI-driven and Hybrid AI-Kalman estimation approaches, highlighting their key characteristics and their performances differences.

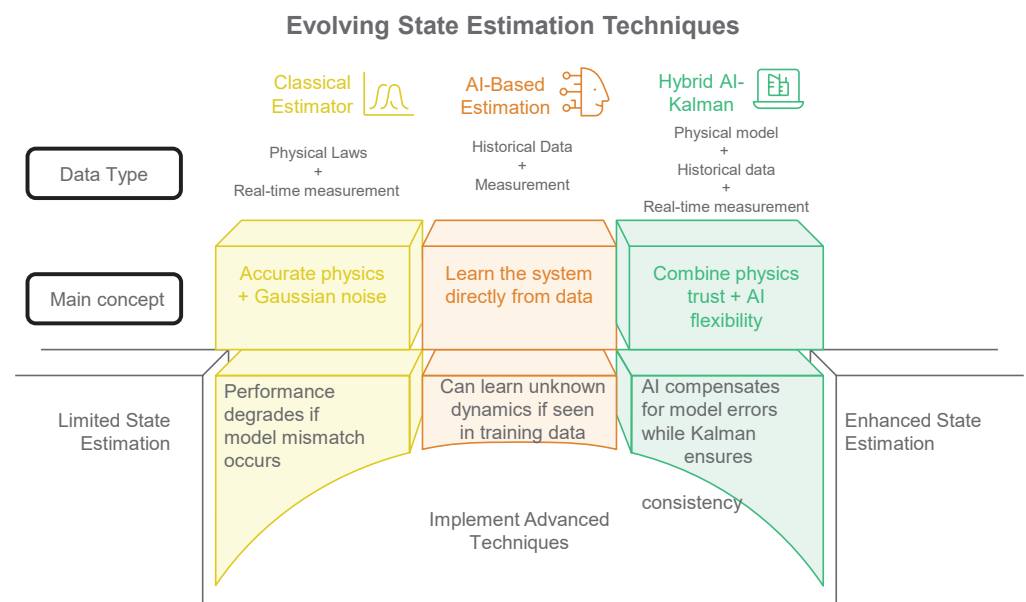


Figure 7. Evolving State Estimation Techniques.

- Extended State Estimation Including Faults:** In traditional Kalman filtering, the system state x_k is estimated from measurements y_k under the assumption of fault-free operation. However, real systems are rarely ideal: sensors drift, actuators degrade, and components wear out. Such faults introduce unknown effects that are not captured by the nominal model, leading to degraded estimation and detection performance.

Hybrid frameworks reformulate the problem as an extended state estimation task, augmenting the state vector to include faults:

$$x_k^a = \begin{bmatrix} x_k \\ f_k \end{bmatrix} \quad (28)$$

where x_k represents the nominal system states, and f_k denotes the fault vector at time step k [45,105–107].

In these architectures, KF provides a structured, recursive estimation framework, while NNs particularly LSTM models learn the temporal evolution of faults. This combination allows accurate, adaptive, and robust fault detection, isolation, and estimation. LSTM models are particularly effective in capturing actuator degradations, sensor drifts, and external disturbances by leveraging tracking error as an anomaly indicator [108,109].

Figure 8 illustrates a typical hybrid extended state estimation framework.

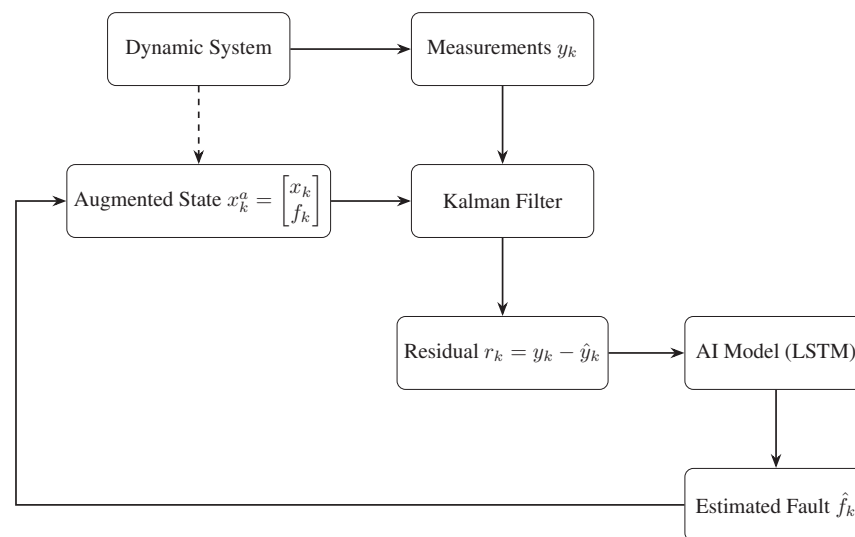


Figure 8. Extended state estimation including faults using a hybrid AI-Kalman approach.

- **Simultaneous State and Fault Estimation (SSFE):** A key advancement in hybrid frameworks is the shift from sequential fault detection to SSFE. This approach explicitly integrates fault variables into the estimation process, capturing the intrinsic coupling between system dynamics and abnormal inputs something conventional decoupled methods often miss.

Traditional observers assume a healthy system and infer faults indirectly from residuals, which can mask early-stage faults and degrade state estimation. SSFE treats faults as part of the augmented state vector, allowing the estimator to maintain high accuracy even in nonlinear, uncertain, or non-Gaussian environments.

Hybrid frameworks often employ RNNs, LSTMs, or Transformers to capture complex temporal relationships in fault evolution. For instance, [110] proposed a hybrid LSTM-EKF method for motor fault detection in a differential mobile robot. The approach combines sequential learning via LSTM with recursive estimation via EKF, using an adaptive weighting factor α_k based on the relative variances of each estimator:

$$\hat{x}_{k+1} = \alpha_k \hat{x}_{k+1}^{\text{EKF}} + (1 - \alpha_k) \hat{x}_{k+1}^{\text{LSTM}} \quad (29)$$

where

$$\alpha_k = \frac{\sigma_{\text{LSTM},k}^2}{\sigma_{\text{EKF},k}^2 + \sigma_{\text{LSTM},k}^2}$$

Here, $\hat{x}_{k+1}^{\text{EKF}}$ and $\hat{x}_{k+1}^{\text{LSTM}}$ are the predicted augmented states from EKF and LSTM, respectively, while $\sigma_{\text{EKF},k}^2$ and $\sigma_{\text{LSTM},k}^2$ denote the estimated variances.

This hybrid weighting ensures that the final state estimate adapts to the reliability of each estimator, enhancing fault detection precision and reducing position errors under high-noise conditions.

- **Residual-Based AI Fault Classification:** Once the hybrid estimator produces residuals, AI techniques can classify and diagnose faults more accurately than traditional thresholding methods. ML models, including feed-forward networks, CNNs, and LSTMs, can be trained to recognize fault signatures embedded in residual sequences. By learning the mapping between residual patterns and fault types or severity, these classifiers improve sensitivity, reduce false alarms, and enable early fault detection, even under noisy or uncertain conditions. The main advantages of the Hybrid AI-Kalman Frameworks are summarized in Figure 9.

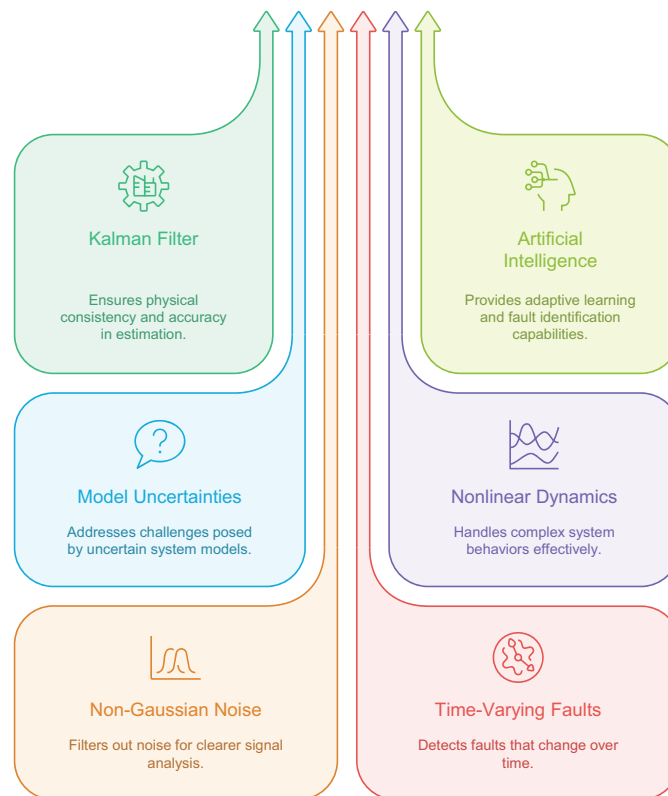


Figure 9. Hybrid AI-Kalman frameworks advantages.

6. Representative Applications

6.1. Power Systems

Power systems represent a major application domain for state estimation and hybrid AI-Kalman frameworks. Reliable monitoring, fault diagnosis, and predictive maintenance are critical to ensuring grid stability, efficiency, and resilience, particularly with the increasing integration of Renewable Energy Sources (RES), such as solar PhotoVoltaic (PV) systems and wind turbines. Conventional Kalman-based estimation methods often face limitations when dealing with nonlinear system dynamics, time-varying noise characteristics, and sen-

sensor faults. Hybrid AI–Kalman approaches address these challenges by integrating physical system models with adaptive and learning-based techniques, enabling more accurate and robust state estimation.

- **Real-time monitoring and fault detection:** Hybrid frameworks enable the estimation of key system states, including bus voltages, generator outputs, and line currents, while simultaneously detecting abnormal operating conditions in real time. Neural networks (NNs), including Long Short-Term Memory (LSTM) networks and attention-based architectures, can capture complex temporal dependencies and compensate for modeling uncertainties. This improves the detection sensitivity for subtle faults, such as incipient transformer degradation, partial line outages, and sensor drift [108].
- **Renewable integration and uncertainty management:** The integration of RES introduces significant variability and non-Gaussian disturbances into power systems. AI-augmented filtering approaches, such as LSTM-EKF and Adaptive Noise Unscented Kalman Filter (ANUKF), can learn nonlinear system behaviors, track time-varying noise characteristics, and dynamically adjust covariance matrices. These capabilities reduce estimation errors and false alarms under changing irradiance, wind conditions, and load variations [99,100].
- **Predictive maintenance and anomaly detection:** Residual signals generated from hybrid estimation frameworks can be further analyzed using AI-based classifiers, such as Support Vector Machines (SVMs), Random Forests (RFs), and neural networks, to identify abnormal behaviors before they develop into critical failures. This enables utilities to perform proactive maintenance, minimize unplanned downtime, and improve operational reliability [101,111].
- **Representative Application–PV generation monitoring:** Large-scale PV farms operate under highly variable environmental conditions, including irradiance fluctuations, temperature variations, partial shading, and sensor inaccuracies. These factors can degrade the performance of conventional model-based state estimation and fault diagnosis approaches. To overcome these limitations, hybrid estimation frameworks that combine physical PV models with artificial intelligence techniques have been investigated [112–114].

Such frameworks have been applied for real-time monitoring and fault detection and diagnosis (FDD) of the DC side of PV systems, addressing the limitations of conventional methods, particularly under low irradiance conditions and during early-stage soft fault detection.

- The experimental evaluation was conducted in MATLAB/Simulink under various weather conditions.
- The proposed approach achieved a classification accuracy of 90.16%, precision of 91.35%, recall of 91.8%, and a near-instantaneous mean detection delay of 0.21 s. Hard open-circuit and short-circuit faults were detected with 100% recall.
- The PV model equations and fault modeling parameters were explicitly provided, ensuring the reproducibility of the reported results [115].

Table 7 presents a comparative overview of hybrid AI–Kalman approaches applied to power system state estimation and fault detection, highlighting their adopted techniques and main advantages.

Table 7. Comparison of hybrid AI–Kalman approaches for power system state estimation and fault detection.

Reference	Application	AI Method	Estimation Technique	Key Advantages
[116]	Smart grid monitoring	LSTM	EKF	Improved fault detection sensitivity; handles nonlinear load dynamics
[99,117]	Wind turbine monitoring	Attention-based neural network	Adaptive EKF	Real-time covariance adaptation; reduces false alarms under variable noise
[100]	UAV power system	CNN-based ProcessNet	UKF	Learns time-varying noise statistics; robust to sensor degradation
[101]	PV farm monitoring	GAN-based adaptive learning	UKF	Online adaptation of Q and R ; enhances predictive maintenance
[110]	Mobile robots with onboard power systems	LSTM-EKF hybrid	EKF	Joint state and fault estimation; reduces position error under high-noise conditions

Hybrid AI–Kalman frameworks provide several practical advantages for power system applications:

1. Improved state estimation accuracy under nonlinear, uncertain, and time-varying operating conditions.
2. Enhanced fault detection sensitivity and robustness against non-Gaussian noise and measurement uncertainties.
3. Real-time adaptability to sensor degradation, changing operating conditions, and renewable energy integration.
4. Improved predictive maintenance capabilities through residual-based AI analysis and classification.

6.2. Industrial Processes

Industrial processes, including chemical plants, manufacturing systems, and automated production lines, rely on accurate state estimation and fault diagnosis to ensure safe operation, high efficiency, and product quality. Traditional model-based Fault Detection and Diagnosis (FDD) methods, including Kalman Filters (KFs) and observer-based approaches, often face challenges due to strong nonlinearities, unmodeled dynamics, time-varying disturbances, and sensor faults. Hybrid AI–Kalman frameworks provide an effective solution by integrating physical process models with AI-driven learning capabilities, improving estimation accuracy, robustness, and adaptability under complex operating conditions.

- **State estimation in chemical processes:** In chemical reactors, distillation columns, and other process systems, critical variables such as concentrations, temperatures, and pressures must be continuously estimated. Hybrid approaches combine process models representing nominal system behavior with AI techniques, such as LSTM networks and neural augmentation methods, to learn deviations caused by unmodeled reaction dynamics, external disturbances, and measurement uncertainties [69,94].
- **Fault detection in industrial systems:** Industrial systems are affected by various faults, including sensor drift, actuator failures, valve malfunctions, and equipment

degradation. Hybrid AI–Kalman methods enhance fault detection performance by combining model-based residual generation with AI classifiers capable of learning complex temporal patterns in residual signals. This enables the early identification of subtle and incipient faults that may remain undetected using conventional approaches.

- **Predictive maintenance and anomaly prediction:** Residual signals generated by hybrid estimation frameworks can be analyzed using machine learning models, such as Random Forests (RFs), Support Vector Machines (SVMs), and Deep Neural Networks (DNNs), to predict the Remaining Useful Life (RUL) of industrial components. This capability supports proactive maintenance planning, reduces unexpected failures, and improves Overall Equipment Effectiveness (OEE).
- **Representative Application–Lithium-Ion Battery State-of-Charge (SOC) Estimation:** Hybrid AI–Kalman approaches have been investigated to improve State-of-Charge (SOC) estimation accuracy for lithium-ion battery energy storage systems. These methods combine the strengths of Kalman filtering for state tracking with the learning capability of neural networks to compensate for modeling uncertainties and changing operating conditions.
 - The Extended Kalman Filter (EKF) provides the initial SOC estimation and generates state information.
 - The LSTM network is trained using EKF-derived state variables, updated estimation errors from the Kalman filtering process, and battery operational data.
 - The LSTM model adapts to uncertainties associated with varying operating conditions.
 - The results demonstrate that the Root Mean Square Error (RMSE) of SOC estimation under different operating conditions was below 0.8%, while the average absolute error remained below 0.5%. The proposed hybrid approach achieved improved estimation accuracy compared with standalone EKF or LSTM methods [118].

Table 8 compares representative hybrid AI–Kalman approaches applied to industrial processes, highlighting their AI techniques, estimation methods, and key advantages.

Table 8. Hybrid AI–Kalman applications in industrial processes.

Reference	Application	AI Method	Estimation Technique	Key Advantages
[69,119]	Chemical reactor	LSTM residual correction	EKF	Improved fault detection; compensates for unmodeled kinetics
[94]	Industrial batch processes	Neural augmentation	EKF	Reduces estimation error under nonlinear disturbances
[96]	Manufacturing system	RNN-aided estimation	EKF	Adaptive tracking of temporal residual patterns; robust to sensor drift
[99]	Process control plants	Attention-based neural network	Adaptive EKF	Dynamic covariance tuning; handles non-Gaussian noise
[101]	Chemical process fault detection	GAN-based adaptive learning	UKF	Real-time adjustment of noise statistics; enhances predictive maintenance

Hybrid AI–Kalman frameworks provide several advantages for industrial systems:

1. Improved estimation of hidden process variables under nonlinear, uncertain, and time-varying operating conditions.
2. Enhanced fault detection capability, including early identification of incipient failures.
3. Increased robustness against measurement noise, sensor degradation, and unmodeled system dynamics.
4. Support for predictive maintenance and process optimization through residual-based AI analysis.

6.3. Robotics and Autonomous Systems

Robotics and autonomous systems require highly accurate state estimation and fault diagnosis capabilities to ensure safety, reliability, and successful operation. These systems typically operate in dynamic, uncertain, and partially observable environments, where conventional estimation techniques alone may not provide sufficient robustness. Hybrid AI–Kalman frameworks have emerged as a promising approach by combining recursive model-based estimation with AI-driven learning capabilities to address nonlinear dynamics, unmodeled disturbances, sensor faults, and time-varying noise.

- **State estimation in autonomous robots:** Mobile robots, drones, and autonomous vehicles depend on accurate estimation of their position, velocity, and orientation for navigation and control. Classical filtering approaches, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), provide effective baseline estimates; however, their performance can be degraded by unmodeled dynamics, wheel slippage, actuator degradation, and sensor misalignment. Neural network-augmented filters, recurrent neural networks, and attention-based architectures have been introduced to learn estimation errors and compensate for these limitations in real time [88,90,94].
- **Fault detection and diagnosis:** Hybrid AI–Kalman methods enhance fault diagnosis in robotic systems by enabling simultaneous estimation of system states and fault-related variables. Representative applications include:
 - Motor degradation detection in mobile robots using LSTM–EKF frameworks [110].
 - Actuator anomaly detection in drones using Split KalmanNet with neural compensation for unmodeled aerodynamic effects [91].
 - Sensor drift detection in autonomous vehicles using attention-based adaptive EKF frameworks [103,120].
- **Simultaneous Localization and Mapping (SLAM):** In SLAM applications, hybrid AI–Kalman approaches improve both robot pose estimation and environmental mapping accuracy. AI components, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, can learn to compensate for sensor noise, dynamic environmental changes, and modeling uncertainties. This enhances robustness in challenging scenarios, including GPS-denied and cluttered environments [89,121].
- **Representative Application–Differential mobile robot:** A hybrid LSTM–EKF framework has been applied for simultaneous state and fault estimation in a differential mobile robot. The proposed approach combines model-based estimation with data-driven learning to improve robustness against uncertainties and actuator faults.
 - The EKF estimates the robot position, orientation, and velocity.
 - The LSTM network learns temporal patterns in the residual signals to detect motor faults.

- An adaptive weighting factor combines the EKF and LSTM predictions, as introduced in Equation (29), where

$$\alpha_k = \frac{\sigma_{LSTM,k}^2}{\sigma_{EKF,k}^2 + \sigma_{LSTM,k}^2}$$

- adjusts the contribution of each estimator according to its uncertainty level.
- The results demonstrate improved fault detection accuracy, reduced position error under high-noise conditions, and enhanced robustness against actuator degradation [110].

Table 9 summarizes representative hybrid AI–Kalman methodologies in robotics and autonomous systems, highlighting their application domains, AI techniques, estimation approaches, and key performance benefits.

- Hybrid AI–Kalman frameworks offer several advantages for autonomous systems:
1. Enhanced estimation of position, velocity, and orientation under nonlinear and uncertain operating conditions.
 2. Early detection and isolation of actuator and sensor faults.
 3. Improved robustness against non-Gaussian noise, sensor degradation, and unmodeled system dynamics.
 4. Support for mission-critical applications, including SLAM, path planning, and autonomous navigation.

Table 9. Hybrid AI–Kalman applications in robotics and autonomous systems.

Reference	Application	AI Method	Estimation Technique	Key Advantages
[88]	Quadrotor	KNODE	EKF	Improved state estimation accuracy; learns unmodeled dynamics
[90]	Autonomous vehicle	LSTM	EKF	Accurate velocity and sideslip angle estimation; compensates modeling errors
[110]	Differential mobile robot	LSTM–EKF	EKF	Joint state and fault estimation; reduces position error under high-noise conditions
[91]	UAV actuator fault detection	Split KalmanNet	KF	Neural compensation for modeling errors; improved fault detection
[100]	Autonomous navigation	ProcessNet	UKF	Dynamic noise adaptation; robust to sensor drift and non-Gaussian noise

7. Comparative Analysis and Discussion

7.1. Performance Metrics

Evaluating state estimation and fault detection performance in hybrid AI–Kalman frameworks requires a systematic set of quantitative metrics. These metrics assess not only the accuracy of state reconstruction but also the reliability, responsiveness, and robustness of fault detection under various system conditions. Selecting appropriate performance metrics

is essential for comparing classical, AI-augmented, and hybrid approaches across different domains, including power systems, industrial processes, and autonomous systems.

- **Estimation accuracy:** The primary measure of a state estimator is the accuracy of its reconstructed state $\hat{x}_k$ compared to the true state x_k . Common metrics include [38,122]:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^N \|\hat{x}_k - x_k\|^2} \quad (30)$$

$$\text{MAE} = \frac{1}{N} \sum_{k=1}^N |\hat{x}_k - x_k| \quad (31)$$

where MAE is the Mean Absolute Error. These metrics provide a straightforward evaluation of overall estimation quality and are frequently used to compare classical KFs with AI-augmented estimators or hybrid approaches.

- **Fault detection performance:** Fault detection performance is evaluated based on how accurately the system identifies abnormal behavior while minimizing false alarms. Key metrics include:
 - **Detection Rate (DR):** The ratio of correctly identified faults to the total number of faults.
 - **False Alarm Rate (FAR):** The ratio of falsely detected faults to the total number of normal events.
 - **Detection Delay (DD):** The time elapsed between the fault occurrence and its detection.

Mathematically, these are expressed as:

$$\text{DR} = \frac{N_{TP}}{N_{TP} + N_{FN}}, \quad \text{FAR} = \frac{N_{FP}}{N_{FP} + N_{TN}} \quad (32)$$

where N_{TP} , N_{FP} , N_{TN} , and N_{FN} denote true positives, false positives, true negatives, and false negatives, respectively [123,124].

- **Robustness metrics:** Robustness evaluates the estimator's sensitivity to noise, modeling errors, and system nonlinearities. Common robustness metrics include:
 - **Normalized Estimation Error Covariance (NEEC):** Quantifies how well the predicted covariance matches actual estimation errors.
 - **Sensitivity index:** Measures how estimation accuracy degrades under increasing noise levels or parameter uncertainty.
 - **Resilience under model mismatch:** Compares RMSE or MAE under nominal and perturbed models to assess adaptation capabilities of AI-augmented filters.
- **Computational performance:** For real-time applications, computational efficiency is crucial. Metrics include:
 - **Execution time per update** (t_{update})
 - **Memory footprint** of the estimator
 - **Scalability:** Ability to maintain performance as the system dimension increases or the number of sensors grows.

- **Trade-offs Between Performance Metrics:**

The performance metrics defined previously are not independent; therefore, their evaluation requires careful consideration of the inherent trade-offs among them. One of the most important operational trade-offs is the balance between the DR and the FAR. Since both metrics are influenced by the same decision threshold, increasing detector sensitivity to improve DR generally results in a higher FAR, whereas reducing

false alarms may increase the number of missed detections. Therefore, the optimal detection threshold should be selected based on operational requirements and the relative cost of false positives and false negatives.

A similar trade-off exists between the RMSE and the MAE as measures of estimation accuracy. RMSE penalizes large residuals quadratically, making it highly sensitive to abrupt faults, transient disturbances, and occasional large estimation errors. In contrast, MAE assigns equal importance to all residuals, providing a more robust indication of overall estimation performance in the presence of persistent low-amplitude deviations or outliers. Consequently, RMSE is more suitable for assessing rapid fault-related estimation degradation, whereas MAE better reflects long-term estimation accuracy under gradual or incipient fault conditions.

- **Metric Suitability by Fault Type:**

The selection of evaluation metrics should be aligned with the characteristics of the fault under investigation. Incipient faults, which develop gradually and generate low-amplitude residuals, are better evaluated using MAE because it captures persistent deviations more effectively than RMSE. Conversely, abrupt faults, such as actuator failures or sensor bias, typically produce larger residuals and require metrics that emphasize significant estimation errors. In such cases, RMSE provides a more appropriate assessment, while DR and FAR remain the primary indicators of fault detection performance. It should be noted that FAR reflects the sensitivity of the detection system rather than the fault category itself.

Table 10 categorizes the main performance metrics according to their strengths, limitations, and suitability for different fault types.

Table 10. Performance metric suitability across fault types.

Metric	Strengths	Limitations	Fault-Type Suitability
RMSE [77,125]	Highly sensitive to large deviations	Sensitive to outliers	Abrupt faults
MAE [126]	Robust to outliers	Gives equal weight to all errors	Incipient faults
DR [127]	Measures fault detection capability	Does not account for false alarms and depends on threshold selection	Abrupt and sensor faults
FAR [128]	Quantifies false alarm frequency	Does not indicate the cause of false alarms; should be interpreted with DR	All fault types

- **Overall assessment:**

Hybrid AI–Kalman methods do not consistently outperform traditional Kalman filters across all evaluation metrics. Their advantages are most evident in fault detection performance, particularly through improved DR, and in estimation accuracy, where lower RMSE and MAE values indicate improved state reconstruction under noisy and uncertain conditions. However, improvements in FAR and Detection Delay (DD) are less consistent and remain insufficiently reported in many studies. Therefore, a comprehensive evaluation of hybrid FDD frameworks requires the joint interpretation of multiple performance indicators, as relying on a single metric may lead to an incomplete assessment of the overall effectiveness of the proposed approach [30,129–131]. Table 11 summarizes commonly adopted performance indicators for evaluating state estimation and fault detection performance in hybrid AI–Kalman frameworks.

Table 11. Performance metrics for state estimation and fault detection in hybrid AI-Kalman frameworks.

Metric	Definition	Evaluation Purpose	Typical Use Case
RMSE [117,118,132]	$\sqrt{\frac{1}{N} \sum_k \ \hat{x}_k - x_k\ ^2}$	Measures estimation accuracy	State reconstruction in robotics, UAVs, and power systems
MAE [110,117]	$\frac{1}{N} \sum_k \hat{x}_k - x_k $	Measures estimation accuracy	Autonomous vehicle localization, industrial process control
Detection Rate (DR) [123]	$\frac{N_{TP}}{N_{TP} + N_{FN}}$	Evaluates fault detection capability	Motor fault detection, sensor drift identification
False Alarm Rate (FAR)	$\frac{N_{FP}}{N_{FP} + N_{TN}}$	Evaluates spurious alerts	High-noise environments, actuator fault detection
Detection Delay (DD) [133]	Time from fault occurrence to detection	Assesses responsiveness	Real-time robotics, power grid fault isolation
NEEC [38,134]	Normalized predicted vs. actual error covariance	Robustness to noise/model mismatch	Adaptive Kalman filters, AI-augmented estimation
Sensitivity Index [123]	Estimation degradation vs. noise/uncertainty	Measures robustness	Nonlinear process monitoring
Execution Time [38]	Computation time per update	Real-time feasibility	UAV navigation, industrial automation
Memory Footprint [135]	Memory requirement of estimator	Resource efficiency	Embedded systems, edge computing

7.2. Interpretability vs. Accuracy Trade-Offs

In the context of state estimation and fault detection, one of the key considerations when integrating AI techniques with classical Kalman filters is the balance between interpretability and predictive accuracy. Classical model-based methods, such as the KF, EKF, or UKF, provide high interpretability: residuals, covariance updates, and state predictions have clear physical meanings derived from the underlying system dynamics. This interpretability is particularly valuable in safety-critical domains such as aerospace, power systems, and industrial automation, where understanding why a decision or detection occurs is as important as the decision itself. Adaptive covariance AI-based estimation represents an intermediate level of interpretability between purely model-based approaches and fully neural network-assisted methods. In these approaches, the Kalman filtering structure remains unchanged, with the prediction and correction steps continuing to rely on established physical models and probabilistic principles. The role of the AI component is limited to estimating or adapting the process and/or measurement noise covariance matrices (Q and R), enabling its impact on the estimator behavior to be explicitly identified and analyzed. As a result, the physical meaning of the estimated states, innovation signals, and covariance propagation is largely preserved, while the estimator gains improved adaptability and robustness against time-varying noise characteristics and modeling uncertainties [136].

However, classical methods often struggle in highly nonlinear systems, non-Gaussian noise environments, or when modeling uncertainties are significant. In contrast, AI-augmented and hybrid frameworks, such as neural network-assisted or LSTM-EKF approaches, can achieve higher estimation accuracy by learning complex system dynamics and noise characteristics directly from data. These methods are capable of capturing nonlinearities, temporal correlations, and fault evolution patterns that classical methods may

fail to model. Because NNs learn nonlinear relationships directly from input data, the resulting state estimates become less transparent, making these approaches generally less interpretable than adaptive covariance-based methods [129].

This improvement in accuracy often comes at the cost of reduced interpretability:

- **Black-box nature of AI models:** NNs, especially deep architectures, operate as black boxes. While they can correct model errors and adapt to evolving system dynamics, the internal feature representations and learned weights lack intuitive physical meaning, making it challenging to explain why a fault was detected or how the state was estimated.
- **Residual interpretation:** In classical KF-based FDD, residuals have a direct statistical interpretation; deviations can be linked to specific sensors or model inaccuracies. In hybrid AI-Kalman approaches, residuals are often adjusted or compensated by neural networks, which can obscure the causal link between a physical fault and the resulting residual.
- **Complexity of hybrid methods:** Hybrid frameworks that combine multiple AI components with Kalman filtering (e.g., LSTM-assisted EKF with adaptive covariance tuning) involve numerous hyperparameters, adaptive weights, and NN architectures. While these frameworks can outperform classical methods in terms of RMSE or fault detection rate, explaining their decisions in a human-interpretable manner is challenging.

Researchers often face a trade-off: increasing accuracy with AI and hybrid methods versus retaining transparency and interpretability with classical approaches. Some strategies have been proposed to mitigate this trade-off:

- **Explainable AI (XAI) integration:** Techniques such as attention maps, feature importance analysis, SHAP (SHapley Additive exPlanations), and LIME (Local Interpretable Model-agnostic Explanations) can be employed to identify the most influential inputs or measurements contributing to state estimation or fault detection decisions. These approaches provide a complementary layer of post-hoc interpretability by offering local or global insights into model behavior without modifying the underlying model architecture. Consequently, they improve transparency and enhance trust in AI-assisted estimation frameworks while preserving their predictive performance.
- **Hybrid modular design:** Separating model-based and AI-based components into distinct modules enables the preservation of interpretable physical residuals while allowing AI techniques to provide nonlinear compensation or adaptive noise modeling. This modular structure improves the balance between interpretability, flexibility, and estimation performance.
- **Physics-Guided Verification:** Data-driven models may generate state estimates that violate the underlying physical constraints of the system [137]. To improve reliability and consistency, recent studies increasingly incorporate physical knowledge into the learning process through approaches such as Physics-Informed Neural Networks (PINNs) or by embedding governing equations and conservation laws directly into the loss function or network architecture. By enforcing these physical constraints, the model is encouraged to produce predictions that are both accurate and physically consistent. In parallel, verification techniques, including interval arithmetic and reachability analysis, are gaining attention as complementary tools for providing mathematical guarantees that neural network outputs remain within predefined safe operating limits under bounded input uncertainties. Together, these approaches enhance the reliability and trustworthiness of AI-assisted state estimation and fault diagnosis systems, supporting their deployment in safety-critical applications [138–140].

- **Post hoc analysis:** Statistical analysis and visualization-based post-processing of neural network outputs can reveal patterns, temporal dependencies, and feature contributions that provide additional insights into AI-assisted corrections and decision-making processes.
- **Rigorous validation:** AI-assisted fault diagnosis systems should undergo comprehensive validation before deployment using robust evaluation strategies, including multi-level performance assessment, benchmarking against existing methods, uncertainty quantification, and cross-validation across diverse datasets. Such validation procedures improve the reliability and trustworthiness of state estimation and fault diagnosis frameworks, particularly in safety-critical applications where incorrect decisions may result in significant operational consequences [141,142].

Table 12 provides a comparative analysis of classical, AI-augmented, and hybrid state estimation frameworks, specifically evaluating the inherent trade-offs between predictive accuracy and model interpretability.

Table 12. Trade-offs between interpretability and accuracy in classical, AI-augmented, and hybrid state estimation frameworks.

Method	Accuracy	Interpretability	Notes/Use Case
Classical KF/EKF/UKF [143]	Moderate (limited by linearization and model errors)	High (physically meaningful residuals)	Suitable for safety-critical applications requiring transparent reasoning
Neural Network-Assisted Estimation [144,145]	High (learns nonlinearities and unmodeled dynamics)	Low (black-box, residuals modified by NN)	UAVs, robotics, and industrial systems with complex nonlinear dynamics
Adaptive Covariance AI-Based Estimation [146]	High (dynamic adjustment to changing noise)	Medium (residuals partially interpretable)	Applications with time-varying or non-Gaussian noise statistics
Hybrid AI-Kalman (e.g., LSTM-EKF, Split KalmanNet) [147–149]	Very High (combines recursive estimation with learned corrections)	Medium-Low (some interpretability through modular design or attention)	Complex fault diagnosis, high-noise environments, robotics, power systems

In summary, the trade-off between interpretability and accuracy remains a key consideration when designing hybrid state estimation and fault detection frameworks. While AI-based methods enhance performance in complex and uncertain environments, careful system design, modularization, and the adoption of explainable AI techniques can help retain a meaningful level of interpretability for decision-making and regulatory compliance.

7.3. Real-Time Implementation Considerations

State estimation and fault detection frameworks, particularly AI-augmented and hybrid approaches, are increasingly deployed in real-time systems such as autonomous vehicles, robotics, industrial processes, and power grids. While these methods offer enhanced accuracy and robustness, their real-time implementation introduces several practical challenges that must be carefully addressed.

- **Computational Complexity:** Classical Kalman filters (KF, EKF, UKF) are computationally efficient and well-suited for embedded applications. However, AI-augmented frameworks, including LSTM-based, neural network-assisted, and attention-driven models, require additional computation for forward passes, gradient updates, or adaptive parameter tuning. In resource-constrained environments, such as microcontrollers or FPGA implementations, careful consideration of model size, network depth, and precision is essential to ensure that state estimation remains within real-time deadlines.
- **Memory and Storage Requirements:** Hybrid AI-Kalman frameworks often store historical data for recurrent neural networks (RNNs/LSTMs) or attention mechanisms to capture temporal dependencies. Large buffer sizes and long temporal windows can significantly increase memory requirements, which may limit deployment on edge devices or embedded controllers. Optimized memory management and sliding window techniques are commonly used to balance estimation accuracy and resource constraints.
- **Latency and Update Rates:** Real-time state estimation requires timely updates to ensure system stability and safe operation. Delays introduced by complex NNs or covariance adaptation routines can affect the responsiveness of the estimator. Techniques such as model compression, pruning, quantization, or approximation of attention mechanisms can reduce latency while maintaining acceptable estimation performance.
- **Sensor Fusion and Data Synchronization:** Many real-time applications rely on multi-sensor data (IMUs, LIDAR, cameras, temperature sensors, voltage/current measurements). Inconsistent sampling rates, communication delays, or packet loss can degrade estimator performance. Hybrid frameworks must incorporate mechanisms to handle asynchronous measurements and ensure proper alignment of data streams.
- **Robustness to Unexpected Inputs:** Real-time systems frequently encounter unforeseen disturbances, sensor failures, or extreme operating conditions. Hybrid AI-Kalman frameworks must maintain stability and accuracy under such conditions. Techniques include:
 - Adaptive thresholds for residual evaluation to prevent false alarms.
 - NN retraining or online adaptation to new operating regimes.
 - Safe fallback to classical KF/EKF when AI predictions are uncertain or inconsistent.
- **Implementation Platforms:** The choice of hardware and software environment influences real-time feasibility. CPU-based implementations are suitable for moderate computational loads, while GPU or FPGA acceleration may be required for deep learning components. Embedded Real-Time Operating Systems (RTOS) provide deterministic scheduling, which is essential for safety-critical systems.

Table 13 evaluates the practical deployment constraints of various state estimation frameworks, comparing their computational load, memory requirements, and overall feasibility for real-time applications.

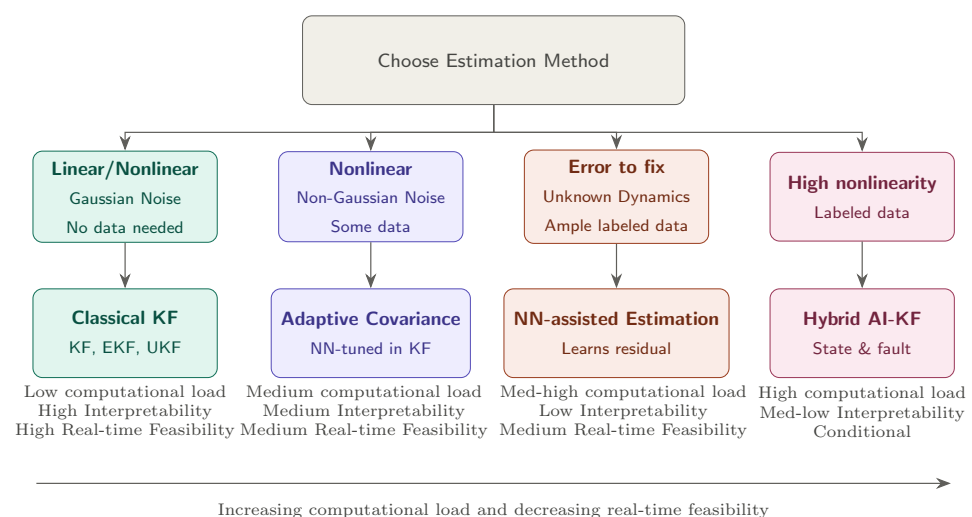
In summary, while AI-augmented and hybrid frameworks significantly improve estimation accuracy and fault detection performance, their real-time implementation requires careful attention to computational resources, latency, memory usage, and robustness. Successful deployment often involves a combination of algorithmic optimization, hardware acceleration, and adaptive system design to ensure that real-time constraints are met without compromising estimation fidelity.

Table 13. Real-time implementation considerations for classical, AI-augmented, and hybrid state estimation frameworks.

Method	Computational Load	Memory Requirements	Latency	Real-Time Feasibility
Classical KF/EKF/UKF [6]	Low	Low	Low	High (suitable for embedded/edge systems)
Neural Network-Assisted Estimation [150]	Medium-High	Medium-High (depends on network size)	Medium	Moderate (may require model compression or GPU acceleration)
Adaptive Covariance AI-Based Estimation [151]	Medium	Medium	Medium	Moderate (requires fast covariance update routines)
Hybrid AI-Kalman (e.g., LSTM-EKF, Split KalmanNet) [147]	High	High	Medium-High	Conditional (depends on hardware acceleration and optimization)

7.4. Practical Guidance for Method Selection

The preceding sections have reviewed classical Kalman filtering, AI-enhanced estimation, and hybrid AI–Kalman approaches, highlighting the trade-offs associated with each method in terms of interpretability, robustness, data requirements, and computational complexity. To provide practical guidance for method selection, Figure 10 presents a decision framework that assists practitioners in selecting an appropriate estimation approach based on four main criteria: the characteristics of system dynamics and noise, the level of model uncertainty, the availability of labeled training data, and the available computational resources. In this context, computational cost is considered as an indicator of real-time feasibility, where lower-complexity methods are generally more suitable for embedded and resource-constrained applications.

**Figure 10.** Decision flowchart for selecting an appropriate estimation framework.

When the system dynamics are well understood and accurately represented by a mathematical model, with process and measurement noise approximately satisfying Gaussian assumptions, classical Kalman filtering approaches remain the preferred choice. The standard Kalman Filter (KF) is suitable for linear systems, while Extended Kalman Filter

(EKF) and Unscented Kalman Filter (UKF) approaches are more appropriate for nonlinear systems. These methods do not require labeled training data, involve relatively low computational cost, and provide complete transparency in the estimation process, making them the most suitable solutions when their underlying assumptions are satisfied.

When the system model remains reliable but the noise characteristics are uncertain, non-Gaussian, or time-varying, adaptive covariance learning provides an effective intermediate solution. In these approaches, the fundamental Kalman filtering structure is preserved, while a lightweight AI model is used to estimate or adapt the process and measurement covariance matrices. This enables the estimator to respond dynamically to changing noise conditions without significantly increasing computational complexity. Since only covariance parameters are learned, these methods typically require limited training data while maintaining much of the interpretability and efficiency of classical Kalman filtering.

When the main challenge arises from uncertain, incomplete, or inaccurate system dynamics rather than noise variations, neural network-assisted estimation becomes a more suitable option. In this case, the neural network learns nonlinear relationships and compensates for modeling errors by estimating residual corrections directly from data. Such approaches can provide significant improvements in estimation accuracy under high model uncertainty; however, they generally require larger training datasets, higher computational resources, and introduce reduced interpretability compared with covariance adaptation methods.

For applications requiring simultaneous state estimation and fault diagnosis under highly nonlinear and uncertain operating conditions, hybrid AI–Kalman frameworks provide a more comprehensive solution. These methods extend the Kalman filtering framework by incorporating AI-based learning components and augmenting the state vector to estimate both system states and fault-related variables within a unified architecture. Although this approach introduces higher computational requirements due to the simultaneous execution of the Kalman estimator and AI model, it preserves the physical structure and recursive estimation principles of the Kalman framework. Therefore, hybrid AI–Kalman methods generally provide a better balance between estimation capability and interpretability compared with fully neural network-based approaches. Their real-time feasibility remains application-dependent and is influenced by factors such as the dimension of the augmented state vector, model complexity, and whether the AI component is executed at every estimation step or periodically. With appropriate implementation strategies, the additional computational burden can often be reduced to satisfy real-time requirements.

8. Open Challenges and Future Research Directions

8.1. Data Scarcity and Labeling

One of the most pressing challenges in AI-augmented and hybrid state estimation and fault detection systems is the scarcity of high-quality, labeled data. Modern ML models, particularly DNNs and recurrent architectures, rely heavily on large datasets to learn accurate system dynamics, noise characteristics, and fault signatures. However, in many real-world domains, such as aerospace, industrial plants, robotics, and power systems, collecting sufficient representative data is difficult due to several factors:

- **Rare Fault Events:** Fault occurrences are, by nature, infrequent in well-maintained systems. This results in highly imbalanced datasets where normal operation dominates and fault examples are limited. Training models on such datasets can lead to bias toward nominal behavior, reducing sensitivity to incipient faults and increasing false negatives.
- **High Cost of Labeling:** Labeling data requires expert knowledge, particularly for complex systems with multiple interacting components. For example, distinguishing

between sensor drift, actuator degradation, or process disturbances often requires domain expertise and detailed post-event analysis, making large-scale labeling expensive and time-consuming.

- **Synthetic Data Limitations:** While simulation and physics-based models can generate synthetic datasets to supplement real-world data, the fidelity of these datasets is limited by model accuracy. Models often fail to capture all nonlinearities, unmodeled dynamics, or noise characteristics, which can result in AI estimators learning unrealistic patterns that do not generalize to actual operating conditions.
- **Privacy and Proprietary Constraints:** Industrial and aerospace datasets often contain sensitive information that cannot be freely shared, limiting access to large-scale multi-source datasets for research or cross-validation. This restriction hampers the development of generalizable AI models.

Several strategies have emerged to address these challenges:

- **Data Augmentation:** Techniques such as adding noise, simulating sensor faults, varying operating conditions, or applying domain-specific transformations can increase dataset diversity and improve model generalization.
- **Semi-Supervised and Unsupervised Learning:** Leveraging unlabeled data through autoencoders, generative models, or clustering allows models to learn latent representations of system behavior without requiring exhaustive labels. Residual-based anomaly detection frameworks often use unsupervised learning to identify deviations from learned normal patterns.
- **Transfer Learning:** Knowledge learned from one system or domain can be adapted to a similar system with limited data. For instance, a neural network trained on one robotic platform can be fine-tuned to another platform using a smaller dataset, reducing the need for extensive labeled samples.
- **Synthetic-to-Real Adaptation:** Domain adaptation techniques bridge the gap between synthetic and real-world datasets, correcting distribution mismatches and improving generalization of AI-augmented estimators to real operating conditions.
- **Active Learning:** In active learning frameworks, the model identifies uncertain or high-impact data points and queries experts for labels. This focused labeling reduces human effort while maximizing model performance.

Table 14 provides an overview of the major challenges associated with data scarcity and labeling in AI-augmented FDD systems, highlighting their impact on AI-based estimation performance and summarizing potential research strategies to mitigate these limitations.

Table 14. Summary of challenges and strategies for data scarcity and labeling in AI-augmented FDD systems.

Challenge	Impact on AI-Based Estimation	Potential Research Direction
Rare Fault Events [152]	Reduced sensitivity to faults; biased models	Data augmentation; semi-supervised learning; synthetic data generation
High Cost of Labeling [153]	Limited labeled datasets; slow model development	Active learning; expert-guided labeling; transfer learning
Synthetic Data Limitations [154]	Poor generalization to real systems	Domain adaptation; hybrid simulation + real data training
Privacy/Proprietary Constraints [155]	Restricted data access; model overfitting to single system	Federated learning; cross-domain adaptation; anonymized datasets

To summarize, addressing data scarcity and labeling challenges is critical for the successful deployment of AI-enhanced state estimation and FDD systems. Although approaches such as active learning, transfer learning, synthetic data generation, and federated learning provide promising solutions, their systematic integration and comprehensive validation within hybrid AI–Kalman state estimation and fault diagnosis frameworks remain limited. Future research should focus on developing strategies that maximize the value of available data, effectively combine synthetic and real-world datasets, and enable robust models with improved generalization capabilities across varying operating conditions and system configurations.

8.2. Robustness Under Uncertainty

A critical challenge for AI-augmented state estimation and hybrid FDD systems is maintaining reliable performance under uncertainty. Real-world systems are subject to a variety of uncertain factors, including unmodeled dynamics, parameter variations, sensor noise, environmental disturbances, and faults that may interact in complex, nonlinear ways. These uncertainties can compromise both the accuracy of state estimates and the reliability of fault detection.

- **Model Uncertainty:** Even in well-characterized systems, mathematical models are inevitably approximations. Simplifications, neglected high-frequency modes, or linearization of nonlinear dynamics can result in residuals that misrepresent true system behavior. AI-augmented estimators can compensate for some model inaccuracies, but excessive deviations between the model and reality may lead to biased state estimates or missed fault detection.
- **Sensor Noise and Measurement Uncertainty:** Non-Gaussian, time-varying, or correlated noise can degrade both classical and AI-augmented estimators. Traditional Kalman filters assume Gaussian noise, and deviations from this assumption can result in miscalibrated residual thresholds. Deep learning-based noise modeling and adaptive covariance estimation have shown promise in addressing these issues, but extreme outliers or abrupt sensor failures still present challenges.
- **Unpredictable Disturbances:** Operational environments often introduce disturbances that were not accounted for during model design or training. Examples include sudden load changes in power systems, abrupt environmental perturbations for autonomous vehicles, or unplanned interactions in industrial processes. Robust AI-enhanced FDD systems must distinguish these disturbances from genuine faults to avoid false alarms.
- **Parameter Variations and Aging Effects:** Physical system parameters can drift over time due to wear, degradation, or environmental changes. Fixed-model estimators may incorrectly interpret these variations as faults, while AI-assisted frameworks can learn adaptive representations to track evolving system dynamics. However, large or rapid parameter shifts remain challenging.

Strategies for Robust Estimation under Uncertainty

Several approaches have been proposed to enhance robustness in the presence of uncertainty:

- **Adaptive Covariance and Noise Modeling:** Techniques such as ProcessNet, GAN-based noise adaptation, and attention-driven covariance tuning allow the estimator to adjust noise parameters dynamically, improving resilience to time-varying or non-Gaussian disturbances [99–101].
- **Ensemble and Hybrid Filtering:** Combining multiple estimators (e.g., EKF, UKF, and LSTM-based predictors) with adaptive weighting can mitigate individual model biases

and enhance robustness under uncertainty. Weighted fusion leverages complementary strengths of different estimation strategies.

- **Residual Analysis with AI Classification:** ML classifiers, including NNs and tree-based models, can learn fault signatures under varying uncertainty conditions, improving discrimination between faults and transient disturbances.
- **Robust Control-Theoretic Integration:** Incorporating H-infinity filters, sliding-mode observers, or other robust control-inspired designs within hybrid AI frameworks can provide performance guaranties under bounded uncertainties, combining theoretical rigor with data-driven adaptability.

Table 15 provides a structured summary of uncertainty sources affecting AI-enhanced FDD systems, highlighting their influence on state estimation and the strategies employed to mitigate their effects.

Table 15. Overview of sources of uncertainty and corresponding mitigation strategies in AI-enhanced FDD systems.

Source of Uncertainty	Impact on Estimation and FDD	Mitigation Strategies
Model Uncertainty [91,94,96]	Biased state estimates; false or missed fault detection	AI-based model compensation; hybrid estimators; ensemble methods
Sensor Noise [100,101]	Miscalibrated residuals; increased false alarms	Adaptive covariance estimation; GAN- or CNN-based noise modeling
Environmental Disturbances [117]	False alarms; residual masking of faults	Residual-based AI classifiers; robust control filters; attention-based feature prioritization
Parameter Drift/Aging [156]	Fault misinterpretation; degradation masking	Online adaptation; adaptive Kalman filters; hybrid AI-Kalman frameworks

Maintaining robustness under uncertainty remains an open research challenge, particularly in complex CPSs with nonlinear dynamics, multi-source noise, and interacting faults. Future work must focus on integrating adaptive AI methods with robust estimation theory to deliver reliable, resilient, and explainable state estimation and fault detection across diverse real-world scenarios.

8.3. Integration with Digital Twins and Cyber-Physical Systems

The integration of AI-augmented state estimation and FDD techniques with DTs and CPSs has emerged as a transformative approach for real-time monitoring, predictive maintenance, and operational optimization. DTs provide a virtual replica of the physical system, enabling continuous simulation, analysis, and interaction with real-world processes. When combined with AI-enhanced estimation and fault detection, DTs can serve as both a predictive and diagnostic tool, offering unprecedented insight into system behavior under uncertainty [157].

- **Digital Twin-Based State Estimation:** DTs allow the deployment of physics-based models that capture nominal system behavior. By integrating AI-enhanced estimators, the DT can dynamically correct model inaccuracies, adapt to changing environmental conditions, and account for unmodeled dynamics. This approach ensures that residuals generated within the DTs framework accurately reflect anomalies rather than modeling errors. NNs, attention mechanisms, and adaptive covariance estimation can be embedded within the twin to refine predictions and improve fault sensitivity [158].
- **Fault Detection in CPS:** CPSs involve tight interactions between computation, communication, and physical processes. Faults in sensors, actuators, or communication channels can propagate rapidly across the system [159]. Hybrid AI-Kalman

frameworks integrated into a CPS architecture enable simultaneous state and fault estimation, ensuring that both physical and cyber components are monitored. Real-time residuals can be cross-checked with DTs simulations, enhancing confidence in anomaly detection.

- **Predictive Maintenance and Prognostics:** By continuously comparing real-time measurements with the DT’s predictions, AI-enhanced FDD methods can identify early signs of component degradation. The integration supports predictive maintenance by quantifying RUL and forecasting potential failure modes. LSTM and RNN-based models within the twin can learn fault evolution patterns, while uncertainty-aware residual analysis ensures reliability under variable operating conditions [160].
- **Closed-Loop Feedback and Control:** In advanced CPS, the DT can provide feedback to control systems. For instance, detected faults or deviations can trigger adaptive control actions, mitigating the impact of failures. AI-augmented state estimation ensures that control decisions are based on accurate, robust, and timely information, even in the presence of noise, uncertainties, or unmodeled dynamics [161].

Table 16 outlines the integration of AI-enhanced state estimation within DTs and CPS, highlighting the specific roles, techniques, and operational benefits for each functional aspect.

The integration of AI-enhanced state estimation and FDD with DTs and CPS represents a significant step toward intelligent, resilient, and self-monitoring systems. However, challenges remain in scaling these approaches for large, heterogeneous systems, ensuring real-time performance, and maintaining trustworthiness of AI predictions in safety-critical applications. Future research should focus on standardized frameworks for twin-based monitoring, uncertainty-aware AI integration, and explainable diagnostics within CPS architectures.

Table 16. Integration of AI-Enhanced State Estimation with DTs and CPS.

Integration Aspect	Role of Digital Twin	AI Techniques Employed	Benefits
State Estimation [162]	Provides nominal model predictions	Neural augmentation, LSTM/RNN, adaptive covariance	Corrects model errors; improves residual fidelity
Fault Detection [163]	Simulates system behavior under nominal	Hybrid AI-Kalman, residual classification	Enhances sensitivity to anomalies; reduces false alarms
Predictive Maintenance [164,165]	Tracks component health and RUL	LSTM prognostics, attention mechanisms	Early detection of degradation; optimized maintenance scheduling
Closed-Loop Control [166,167]	Real-time decision support	Adaptive filtering, attention-driven feature selection	Enables fault-tolerant control; maintains operational safety

9. Conclusions

This review has comprehensively examined state estimation-based FDD methodologies, with a particular emphasis on the integration of AI techniques to enhance classical estimation frameworks. The landscape of approaches spans from traditional model-based estimation to AI-augmented methods and hybrid AI-Kalman frameworks, each with distinct strengths, limitations, and application domains.

Classical model-based methods, such as KF, EKF, UKF, and linear observers, provide physically interpretable residuals and have been widely applied across industrial,

power, and robotic systems. Their key advantage lies in the transparency of the estimation process and computational efficiency. However, these methods are fundamentally constrained when faced with nonlinear dynamics, time-varying parameters, modeling uncertainties, or non-Gaussian noise. Linearization errors, sensitivity to unmodeled disturbances, and systematic biases in residuals limit their adaptability and reliability in complex real-world environments.

AI-augmented estimation techniques address these limitations by learning unmodeled system dynamics, compensating modeling errors, and adapting noise covariance in real time. Frameworks such as Split KalmanNet, Neural Augmentation, RNN/LSTM-assisted estimators, and ProcessNet demonstrate significant improvements in robustness, accuracy, and adaptability, particularly under nonlinear and uncertain conditions. The integration of attention mechanisms and online adaptive learning further enhances performance by enabling estimators to focus on the most informative and reliable sensor measurements, even as operating conditions evolve over time.

Hybrid AI-Kalman frameworks merge the interpretability of classical estimators with the temporal learning and pattern recognition capabilities of AI. These frameworks facilitate simultaneous state and fault estimation, improve residual-based fault classification, and allow adaptive weighting of multiple estimators based on real-time uncertainty. Applications in autonomous robotics, smart grids, and industrial CPS show that hybrid approaches consistently outperform purely classical or purely data-driven methods, particularly in complex, high-noise, and fault-prone scenarios. By combining physical consistency with AI-driven adaptation, hybrid frameworks achieve a balance between robustness, accuracy, and operational interpretability.

A comparative assessment highlights inherent trade-offs across these paradigms. Classical estimators excel in transparency and computational efficiency but struggle with complex, uncertain, or non-Gaussian environments. AI-augmented approaches improve robustness and adaptivity but require substantial training data and may compromise interpretability. Hybrid frameworks offer a balanced compromise, leveraging physical modeling and AI learning, though their complexity and need for online adaptation pose practical implementation challenges. Real-time feasibility, sensor reliability, and seamless integration with existing industrial, power, and robotic systems remain critical factors for successful deployment.

Despite significant progress, several challenges remain for future research. Data scarcity and the difficulty of acquiring high-quality labeled fault datasets continue to constrain data-driven approaches. Ensuring robustness under uncertainty, particularly in the presence of time-varying noise, unmodeled dynamics, and non-Gaussian disturbances, remains an open problem. Integration with DTs and CPS to enable real-time simulation-informed estimation is still nascent. Additionally, the development of XAI frameworks that maintain interpretability while achieving high accuracy is essential for safety-critical applications.

Looking forward, promising research directions include the development of self-adaptive, online AI-Kalman filters capable of continuous learning from streaming data, as well as the integration of hybrid PINNs for modeling nonlinear and uncertain systems more accurately. Multi-modal sensing combined with attention mechanisms holds potential for improving real-time state estimation and fault detection. Scalable architectures for large-scale industrial, power, and autonomous robotic systems will be critical for translating laboratory advances into real-world applications.

In conclusion, the evolution from classical model-based FDD to AI-augmented and hybrid frameworks illustrates a clear trajectory toward intelligent, adaptive, and resilient fault diagnosis systems. By combining physical models with advanced AI techniques, mod-

ern approaches achieve enhanced estimation accuracy, robust fault detection, and real-time adaptability, effectively addressing the complexities inherent in modern CPSs. Continued research into adaptive, explainable, and scalable methodologies will be crucial for meeting the operational demands of next-generation industrial and autonomous systems.

Funding: This research received no external funding

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

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