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Adaptive Design of Alarm Systems in Industrial Processes

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Abstract:
Alarm systems in industrial process control are critical for ensuring safety and efficiency, alerting operators to potential process deviations or failures. This paper introduces a novel methodology for the real-time optimization of alarm systems, particularly for distributional shifts in the process variables. Our approach is divided into two phases: the design phase, which uses historical data to establish key performance indices such as missed alarm rate and false alarm rate; and the application phase, which adapts to real-time data with initially unknown statistical properties. The case study on the process variable demonstrates the effectiveness of our method in detecting distributional shifts and enhancing alarm system performance at runtime. This study offers a significant contribution to the field of industrial alarm management, providing a scalable framework for dynamic environments.

Keywords: Alarm Systems, Adaptive Design, Distributional Shift, Statistical Difference Measures

1. INTRODUCTION

The landscape of industrial monitoring has significantly evolved with the advent of sophisticated systems like Supervisory Control and Data Acquisition (SCADA) and Centralized Monitoring Systems (CMS). These systems, equipped with a plethora of sensors, play a pivotal role in condition monitoring and system state identification through predefined thresholds Izadi et al. (2009). Alarm systems, integral to these monitoring frameworks, are tasked with signaling abnormal states, often resulting from component malfunctions or faults. The efficacy of these alarm systems is crucial, not only for operational performance but also for maintenance cost-effectiveness, especially in industries with accessibility challenges such as offshore wind farms May and McMillan (2013). Alarm management emerges as a complex challenge, particularly in scenarios where numerous alarms can be activated concurrently Wang et al. (2016). Historical incidents, such as the Three Mile Island nuclear accident, underscore the consequences of alarm system failures, where operators were overwhelmed with redundant and misleading information Zang et al. (2015). To enhance safety and efficiency, various methodologies, tools, and metrics have been developed. Notably, indices like Averaged Alarm Delay (AAD), Missed Alarm Rate (MAR), and False Alarm Rate (FAR) are employed to assess the performance and safety of alarm systems in abrupt fault scenarios Xu et al. (2011). In the realm of intermittent faults and mixture processes, a novel time-variant finite mixture model has been proposed to statistically model process variables affected by intermittent faults, offering new insights into FAR and AAD calculations, and introducing a dynamic MAR metric Asaadi et al. (2022). Innovations in alarm system design include the development of generalized delay timers and the use of Markov models for performance evaluation, comparing traditional and advanced delay timer systems in terms of FAR, MAR, and Expected Detection Delay (EDD) Adnan et al. (2013). Furthermore, the assessment of monitoring systems with adaptive alarm thresholds has been advanced through the integration of semi-Markov processes and temporal logic gates Aslansefat et al. (2020a). Additionally, new techniques for optimizing alarm filters, which consider plant and control system information, have been proposed, allowing for more flexibility in meeting independence requirements Roohi et al. (2021).

1.1 Alarm System Limitations and the Need for Adaptive Design

Alarm systems in industrial settings, such as manufacturing plants and power generation facilities, are essential for signaling abnormal conditions that necessitate immediate operator intervention. These systems enhance safety and operational efficiency EEMUA (Sep. 2019). However, traditional alarm systems are often plagued by issues like alarm flooding, where numerous alarms are triggered simultaneously, overwhelming operators and hindering effective response Yang et al. (2022). Additionally, static alarm settings may not be optimal across different operational conditions, leading to false or missed alarms Yang et al. (2022).The dynamic nature of industrial processes calls for a more adaptable approach to alarm management. Adaptive alarm systems, which adjust their settings in response to the current process state, have shown promise in reducing false alarms and enhancing system reliability Bauer et al. (2011). These systems are particularly beneficial in complex and distributed environments, where fault-tolerance levels significantly impact the trustworthiness of network-based monitors Mustafa et al. (2023). Moreover, adaptive systems can implement sophisticated shutdown procedures, such as graduated warnings, offering advantages in scenarios where a simple emergency stop is insufficient Gyasi et al. (2023).

This paper introduces an adaptive alarm system design that addresses distributional shifts in real-time process variables. We utilize statistical difference measures to automatically adjust the alarm system configuration in response to significant shifts. Our objective is to enhance alarm management system efficiency and reliability, specifically mitigating the impact of these shifts during run-time. We validate our approach through a real-world industrial case study, demonstrating its practical applicability.

2. PROBLEM FORMULATION

2.1 Detecting Alarm States

Alarm state detection often involves comparing a process variable, $x(t)$, against set high (x_{htp}) and low (x_{ltp}) trip points. The alarm variable, $x_a(t)$, is defined as:

$$x_a(t) = \begin{cases} 1 & \text{if } x(t) > x_{htp} \text{ or } x(t) < x_{ltp}, \\ 0 & \text{if } x_{ltp} \leq x(t) \leq x_{htp}. \end{cases} \quad (1)$$

Fig. 1 illustrates the schematic of the alarm generation mechanism within an alarm system. It is represented through two time-series plots: the upper plot displays the behavior of the process variable, $x(t)$, as a function of time, t, and the lower plot indicates the corresponding state of the alarm variable, $x_a(t)$.The process variable, $x(t)$, is shown as a fluctuating continuous function over time. The predefined alarm threshold level is denoted by a dashed horizontal line at x_{tp}. When the process variable exceeds this threshold, that is, $x(t) > x_{tp}$, the alarm variable, which is binary in nature, transitions from a value of 0 (representing an inactive alarm state) to a value of 1 (indicating an active alarm state). This change in the alarm variable's state occurs at time t_0, the instant when $x(t)$ crosses the threshold x_{tp}. The alarm remains in an active state, with $x_a(t) = 1$, for the duration that $x(t)$ remains above x_{tp}. For a comprehensive discussion on alarm state detection methods, refer to Asaadi et al. (2023).

2.2 Abrupt Faults

Consider a process variable in a normal state with distribution $p(x)$. An abrupt fault alters its statistical properties, such as the mean, changing the distribution to $q(x)$ in the faulty state. The probability density functions (PDFs) for normal ($p(x)$) and abnormal ($q(x)$) states are illustrated in Fig. 2.

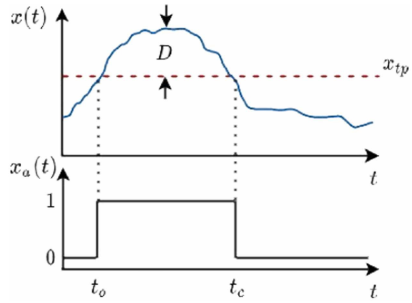


Fig. 1. Samples of a process variable alongside the alarm trip. Gyasi et al. (2023)

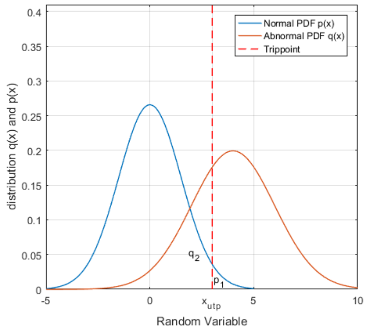


Fig. 2. Normal ($p(x)$) and abnormal ($q(x)$) PDFs

Alarm performance indices like False Alarm Rate (FAR) and Missed Alarm Rate (MAR) are critical. FAR, indicated by p_1, represents the likelihood of a false alarm in normal conditions, while MAR, denoted by q_2, signifies the probability of missing an alarm in abnormal conditions Xu et al. (2011). These are calculated as:

$$\text{FAR} = p_1, \quad \text{MAR} = q_2. \quad (2)$$

3. METHODOLOGY FOR A SAFELY DESIGNED ALARM SYSTEM

The primary objective of this study is to establish a robust framework for designing alarm systems that can effectively handle abrupt faults. Illustrated in Fig. 3, our proposed methodology encompasses two distinct phases: the design phase and the application phase.

3.1 Design Phase

The design phase is an offline process utilizing historical data to develop an alarm system. This system is tailored based on key performance indices such as the missed alarm rate, false alarm rate, and average alarm delay. This phase involves employing a change detection method for the process variable to formulate these performance indices. Subsequently, the optimal design parameters are archived for future reference and comparison.

3.2 Application Phase

Conversely, the application phase adopts an adaptive strategy, processing real-time data whose statistical properties are initially unknown. For instance, in monitoring the pressure of a thermal power plant's main steam turbine,

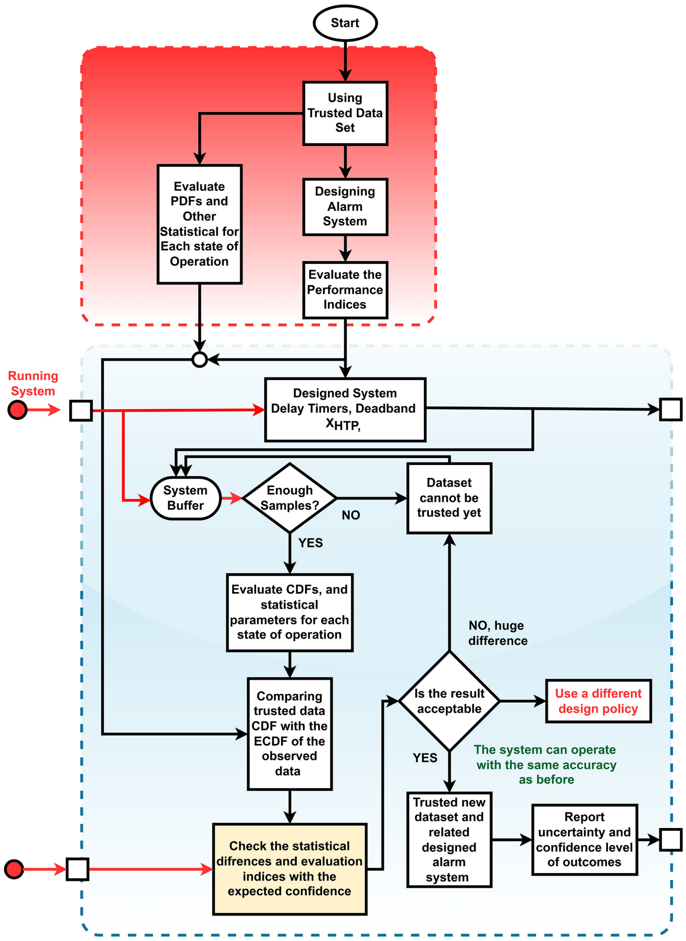


Fig. 3. Flowchart of the proposed approach

the alarm system is configured to promptly signal abrupt faults with minimal delay. However, the classification of incoming data as faulty or non-faulty remains uncertain in this phase. This uncertainty necessitates the estimation of the probability density function (PDF) and statistical parameters for each class as data is acquired. A buffer of samples might be required for accurate statistical differentiation. Utilizing the modified Chernoff error bound, as detailed in Aslansefat et al. (2020b), we compare the operational state's statistical similarity between the design and application phases. The challenge lies in overlap in the PDFs of the real-time data within the sliding window and the historical trusted data. The likelihood of error can be expressed as:

$$\mathrm{P}(error) = \int_{-\infty}^{\infty} \mathrm{P}(error|x)P(x)dx, \tag{3}$$

where $P(error|x)$ is the minimum probability of run-time data within the sliding window and the offline faulty data. The error probability can be further dissected into two parts, representing FAR and MAR, respectively. The relationship between error likelihood and the statistical difference between two states' cumulative distribution functions (CDFs) is crucial. This relationship can be used to predict run-time errors using Empirical Cumulative Distribution Function (ECDF) based statistical measures like the Kolmogorov-Smirnov distance (KSD) Deza and Deza (2014); Raschke (2011).

$$\mathrm{P}(correct) \approx 1 - \mathrm{KSD} = 1 - \sup_{x} \left(\mathrm{F}_{runtime}(x) - \mathrm{F}_{NS}(x)\right). \tag{4}$$

The error probability, P(error), is the complement of $P(\text{correct})$ which itself is approximately the complement of the Kolmogorov-Smirnov Distance (KSD), where is calculated as 4. Here, $F_{\text{run-time}}(x)$ represents the empirical cumulative distribution function of the run-time data, and $F_{\text{NS}}(x)$ denotes the cumulative distribution function of the fault-free normal state data used in the system's design phase. For more detailed explanations on the above formula readers are encouraged to study Asaadi et al. (2023). A minimal statistical discrepancy (low p(error)) indicates a high degree of reliability in the alarm system's operation and precision, as determined during its design phase. Conversely, a pronounced statistical discrepancy questions the system's reliability, suggesting the need for a revised design strategy or manual re-calibration of the system. Furthermore, should the divergence between operational data and validated data exceed a predetermined threshold, it should not be misconstrued as a shift in distribution but rather as an indication of a malfunctioning state. In other words, two predefined thresholds are utilized to classify the streaming data within the sliding window. mathematical relation 5 elucidates the aforementioned explanation with greater clarity.

$$\mathrm{P(error)} = \begin{cases} \text{Similar Data}, & \text{if } 0 \le \mathrm{P(error)} \le Th_f \\ \text{DS Detected}, & \text{if } Th_f < \mathrm{P(error)} \le Th_s \\ \text{Faulty Data}, & \text{if } Th_s < \mathrm{P(error)} \end{cases} \tag{5}$$

The utilization of two predefined thresholds is essential for distinguishing between types of dissimilarities, as a faulty situation represents a distinct type of dissimilarity, often completely different from other variations. Consequently, these thresholds are instrumental in determining whether the observed dissimilarity in data is attributable to a fault or merely represents a minor distributional shift (DS) in the behavior of the process variable.

The pseudo-code presented provides a structured overview of the proposed "Safe Designed Alarm System". It delineates the systematic process from the initial design phase, utilizing historical data, to the application phase, where real-time data classification and continuous evaluation ensure the system's adaptability and reliability. It is noteworthy that the adaptive design of alarm systems can serve as a proactive alert to operators, enhancing their ability to discern false alarms. Consider a scenario in which an operator receives an alarm; concurrently, the adaptive system indicates a necessary adjustment in the threshold, revealing that the process variable remains within its normal operational range. Consequently, this allows the operator to recognize that the triggered alarms are false and can be disregarded.

3.3 Statistical Difference Measures

This section introduces statistical distance values for the application phase in the flowchart's comparison stage, as shown in the yellow box of Fig. 3. A buffer, sized by an expert at design time, accumulates samples to reflect the operation state's statistical characteristics. The future data, not assigned to a specific operation state, is analyzed post-collection using the previously designed

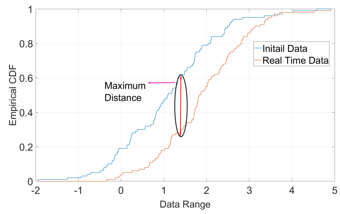
Algorithm 1 Safe Designed Alarm System

```
procedure Main
    DesignPhase
    ApplicationPhase
end procedure
procedure DesignPhase
    Design alarm system based on historical data
    Archive design parameters
end procedure
procedure ApplicationPhase
    while true do
        Classify online data through the designed alarm system
        Extract statistical parameters and ECDF of run-time data
        Compare statistical differences with historical data
        if results are acceptable then
            Continue operation with current alarm system
        else
            Notify operator or re-initiate DesignPhase
        end if
    end while
end procedure
```

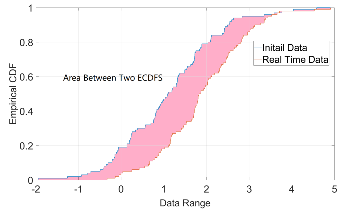
alarm system to identify the operation state based on generated alarms. Buffered data statistical properties are compared to the initial dataset using ECDF-based measures like Kolmogorov Smirnov (KSD), and Wasserstein (WD)Deza and Deza (2014). The design phase involves setting expected confidence levels for these measures and calculate P(error) in 4. Three scenarios are considered based on confidence comparison: 1) Collect more data if confidence is slightly below the threshold; 2) Invoke human intervention if confidence significantly exceeds the threshold; 3) Accept the alarm system's findings if confidence is slightly above the threshold. An example is a process variable affected by natural noise, leading to varying alarm counts and necessitating operator assessment or system redesign. Fig. 4 illustrates these statistical measures, drawing inspiration from Aslansefat et al. (2021). The KSD measures the maximum difference between two ECDFs, while the WD is more sensitive to distribution shape changes, Aslansefat et al. (2021); Asaadi et al. (2023). These statistical distances aid in real-time adjustment of the alarm system's design parameters, enhancing its performance.

4. CASE STUDY

In this case study, we focus on the analysis of a process variable named 'HU21212121R101T2U', which represents the input flow to a tank. Our objective is to preprocess this time series data, detect change points, and analyze the operational zones to improve alarm system performance at its run-time.While various change point detection techniques are available, it's important to note that in this paper, we do not delve into the details of change detection methods. Instead, we employ a simple mean value change detection approach to divide the data into two distinct operational zones: Faulty and Fault-Free, Fig. 5.The segmented data was then analyzed separately. For the Fault-Free zone, we characterized the typical behavior



(a) The KSD



(b) The WD

Fig. 4. Statistical Difference Measures

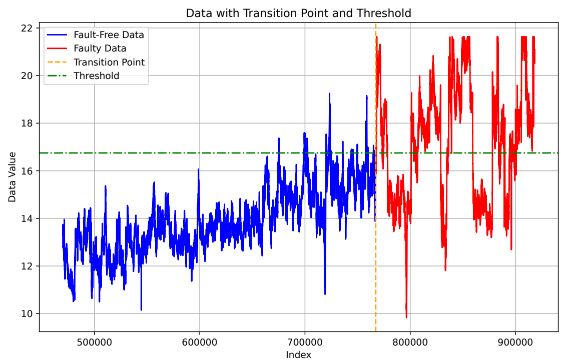


Fig. 5. Process variable 'HU_2121_2121_R101_T2_U'

of the process variable. In contrast, the Faulty zone data was found to exhibit a mixture of distributions, indicating complex underlying dynamics. Histograms of both fault-free and faulty data sets were generated to visualize the distribution of data points in each operational state. These histograms provide insights into the variability and typical behavior of the process under different conditions Fig. 6, and Fig. 7. Given the complexity of the Faulty data, we

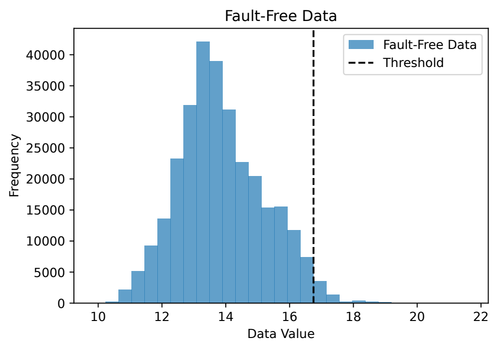


Fig. 6. Histogram of fault-free data.

applied the Expectation-Maximization (EM) algorithm to estimate the parameters of the underlying Gaussian Mixture Model (GMM). This approach provided a robust

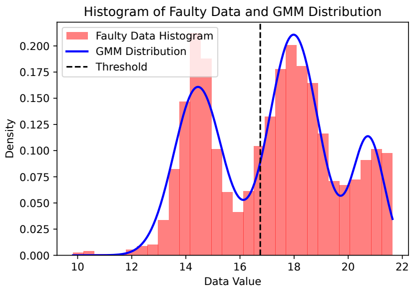


Fig. 7. Histogram of faulty data.

statistical framework to understand the variability in the Faulty operation zone.

Expectation-Maximization Algorithm

The Expectation-Maximization (EM) algorithm is a recursive technique used to obtain the maximum likelihood or maximum a posteriori (MAP) estimates for parameters within statistical models that include unobserved or hidden variables. This method involves two main phases in its iteration: the expectation (E) step and the maximization (M) step. In the E step, a function is constructed to represent the expected value of the log-likelihood, which is calculated using the current parameter estimates. Following this, the M step involves optimizing the parameters to maximize this expected log-likelihood as determined in the E step. The updated estimates of the parameters are then utilized to infer the distribution of the latent variables for the subsequent E step. Given a statistical model with observed data X, unknown parameters θ, and latent variables Z, the likelihood function is $L(\theta; X, Z)$. The goal is to maximize the marginal likelihood of the observed data:

$$L(\theta; X) = \sum_{Z} L(\theta; X, Z)P(Z|X, \theta) \qquad (6)$$

Algorithm Pseudocode

Algorithm 2 Expectation-Maximization

1: Initialize the parameters $\theta^{(0)}$
2: **repeat**
3:    **E-step**: Estimate the latent variables Z given current parameters $\theta^{(i)}$
4:       $Q(\theta|\theta^{(i)}) = \mathbb{E}_{Z|X,\theta^{(i)}}[\log L(\theta; X, Z)]$
5:    **M-step**: Update the parameters θ
6:       $\theta^{(i+1)} = \arg\max_{\theta} Q(\theta|\theta^{(i)})$
7:    $i \leftarrow i + 1$
8: **until** convergence

The analysis includes two histograms representing the distributions of fault-free and faulty data, respectively. Both histograms include a threshold line at $x = 16.74$, facilitating the identification of data points that exceed this threshold.

4.1 Threshold Adjustment for Alarm System

Utilizing the insights gained from the distribution analysis, we adjusted the threshold levels for the process variable's alarm system.

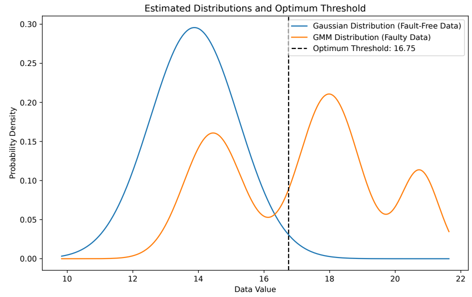


Fig. 8. Adjusted threshold at the design phase of the algorithm.

4.2 Adaptive Design Consideration

Our analysis highlighted the need for an adaptive design approach in managing this process variable. This involves continuously monitoring the data, updating the statistical models, and adjusting the thresholds dynamically to accommodate changes in the process behavior.In the proposed algorithm for the adaptive design of alarm systems, we analyze the distribution of fault-free (normal) data. A key step involves defining a sliding window on the run-time. This approach allows us to dynamically analyze segments of the data over time.As part of our case study, we focused on a specific segment of the time series data, which included 4000 samples prior to the transition point, representing the normal operational zone. We employed a sliding window technique for real-time data analysis, characterized by a window length of 200 samples and a shift of 65 samples. This means that after every 65 samples, the window was updated to include the latest 200 samples. The KSD was calculated for the samples within each sliding window and compared with the KSD values obtained from 10 percent of the fault-free data.Further, to adjust the threshold settings of the alarm system, we utilized the Receiver Operating Characteristic (ROC) method. This approach was particularly useful given the limited availability of online faulty data, prompting us to use data within the sliding window and offline faulty data for our analysis. This method enhances the adaptability and responsiveness of the alarm system, enabling it to detect irregularities more effectively by continuously comparing current data trends against established normal patterns.The results of our study are illustrated in the following figures. Fig. 9 shows the KSD calculated for the sliding window compared to the fault-free data, and Fig. 10 displays the process variable with the thresholds over the 4000 sample segment.

5. CONCLUSION

This study has successfully demonstrated a comprehensive approach to alarm management and adaptive design of alarm systems. Our methodology, which encompasses both design and application phases, leverages historical data and real-time processing to optimize alarm system performance. Key performance indices such as missed alarm rate, and false alarm rate were central to our system's design, ensuring a balance between sensitivity and specificity.Through the case study of the process variable 'HU212121 21R101T2U', we illustrated the effectiveness

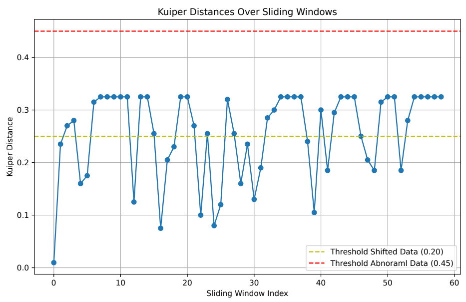


Fig. 9. KSD for the samples within the sliding window

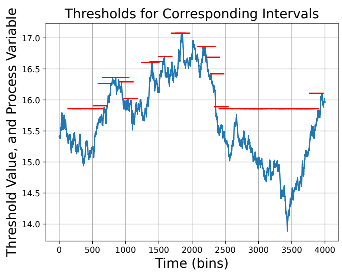


Fig. 10. $x(t)$ (in blue) graph showing the calculated thresholds (in red)

of our approach in distributional shift zones. The use of various statistical distance measures, including the KSD, has proven instrumental in enhancing the robustness and efficiency of alarm systems, particularly in environments with distributional shifts.Our findings underscore the importance of adaptive alarm systems in industrial process control. The ability to dynamically adjust to changing conditions and maintain high levels of accuracy in fault detection is crucial for process safety and efficiency. Future work should focus on further refining these methods and exploring their applicability in a broader range of industrial scenarios.

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