Key Elements to Contextualize AI-Driven Condition Monitoring Systems towards Their Risk-Based Evaluation

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***Abstract*— Industrial users can be justifiably hesitant in adopting Condition Monitoring Systems (CMSs) unless evidence indicates benefits from their use. Measuring a CMS's ability to prevent losses is difficult and lacks standard procedures. The increasing availability of closed-box Artificial Intelligence (AI)-driven CMSs exacerbates the hesitancy as predicting their impacts is more challenging. This paper details three key elements critical to evaluating CMS impact: (1) the *Application Area*, (2) the *Risk Management Processes*, and (3) the *Monitoring Mechanism*. This paper discusses these elements in their capacity to contextualize a CMS's role within an asset's risk management processes, which can lead to justifying CMS use.**

Keywords—condition monitoring systems, algorithm evaluation, asset management, risk assessment, production maintenance

I. Introduction

Enterprises seek tools and technologies to efficiently manage their assets. The value of a tool in managing a specific asset comes from its impact on the asset needs. Proper evaluation procedures capture this information by describing and justifying both the value and impact of a tool, alleviating any skepticism in the tool's worth and adoption potential. In this paper, we consider the evaluation of Condition Monitoring Systems (CMSs). CMSs are tools that help mitigate asset faults, failures, costly repairs, and unexpected downtime by monitoring for detrimental changes in asset health or risk state (see Fig. 1 for a manufacturing case).

Two hurdles stand in the way of accurately measuring or evaluating a CMS's risk-mitigating impacts. First, no widely accepted method for assessing a CMS in terms of mitigated risk exists. Second, an increasing number of CMSs rely on machine learning, and their closed-box, also known as 'black box,' nature makes evaluation a challenge. Closed-box AI-driven CMSs have the appeal of providing more monitoring opportunities for cheaper investments, driving a paradigm shift away from human-driven condition monitoring towards more automated, computer-based approaches [12,13,14]. However, these CMSs have obfuscated internal logic due to complexity or intellectual property concerns [5,9], impeding evaluations for impact and investment returns [2,3,4].

Risk-based evaluation can build trust in a CMS and justify its investment by demonstrating differences in risk with and without a CMS. The differences suggest risk-mitigating capabilities provided by the CMS to any asset and its existing risk management processes. To this end, we contextualize a CMS's role in risk management processes of an industrial asset and use this context to explain a CMS's risk-reducing impacts. This paper describes key elements that provide:

- the context for the CMS's risk-reducing objective;
- insight into the configuration of the CMS during design and operation; and
- the importance of these elements in evaluating a CMS.

II. Key elements to contextualize a condition monitoring system

Fig. 2a-b show the shared key elements between the design phase and operations of an asset that capture the context needed for explaining and evaluating the impacts of a CMS: (1) Application area, (2) Risk management processes, and (3) Monitoring mechanism. These elements provide the monitoring scope and boundaries on the asset(s) or system(s), risk-mitigating objectives and processes that may be affected by monitoring, and tool implementation for condition monitoring. In addition, this division specifies the role of a CMS as part of an asset's monitoring mechanism. This division distinguishes influences on CMS performance due to changes in a particular asset or shifts in its risk management.

The first key element, the application area, includes the asset subject to condition monitoring and any stakeholders deciding the asset's design and operation. For example, the application area consists of the physical production setup and any sensory apparatus that tracks condition indicators in a manufacturing setting. The decision-making personnel design and operate the manufacturing system.

The second element, risk management processes, describes mechanisms in the asset to sense, process, and act on hazards, emphasizing interactions with the CMS. Risk management processes involve risk identification, monitoring, evaluation, and treatment [6]. Each process requires specifications for its functionalities, logistics and information flow, and relevant technologies and personnel.

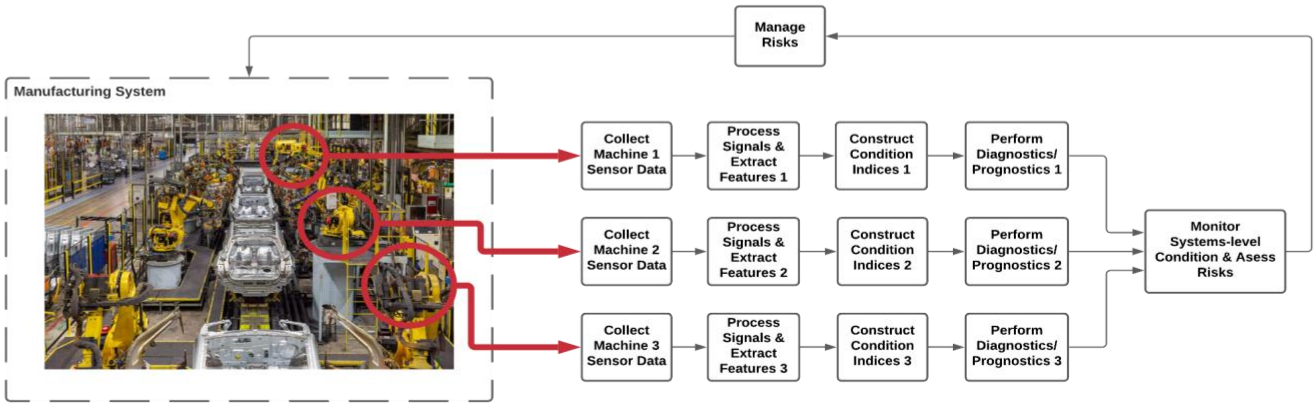

Fig. 1. Conceptual model of using condition monitoring data for risk mitigation in a multi-stage manufacturing setting, such as the depicted production line.[1] Data collected and analyzed from the machines in the manufacturing system ultimately provides feedback to manage the system's risks.

Finally, the monitoring mechanism element describes the usage of collected asset-related information to inform the asset's risk management processes on the occurrence and severity of hazardous scenarios [16]. An automated CMS enables dynamic monitoring to assess risk and issue early operational warnings [18]. Continuing the manufacturing example, an automated CMS can be a production system's mechanism to monitor and assess machine degradation in an evolving environment [17].

III. Key Element Configurations Between Design & Operations

Risk management processes change as you move from the design phase of an asset to its operations. The design focuses on identifying potential hazards and risks, establishing plans for the risk management processes, and assembling tools and technologies to address potential hazards and risks. Conversely, operations focus on executing those management processes to track and mitigate risks. This difference influences the structure and evolution of the three key elements, especially regarding their logistics and information flow, that contextualize a CMS's impact. We focus on these differences in this section, using Fig. 2-a and 2-b to represent the design and operations phases, respectively.

A. *Design Phase*

Fig. 2-a depicts the design phase's decision-making process that generates a plan that addresses risk management processes for asset operations. In this block diagram, each key element comprises components or functions required by components. Links between these components delineate actions, information, or decision signals.

The components in the first key element, the application area, include the decision-maker(s) and the asset's physical configuration. The decision-maker reviews and decides the extent of risk management for their asset. This review incorporates identified risk scenarios, business impacts, risk treatment measures for the asset, and CMS-related issues, such as algorithm selection, sensing capabilities, and risk representation. Analysis of the asset's physical configuration provides boundaries for identifying and assessing asset risks and requirements for sensing and condition monitoring.

Risk management processes, the second key element, require design choices for risk evaluation and treatment. Risk evaluation should be compatible with the type and nature of incoming CMS data. The resulting representation of risk from the evaluations should match protocols based on user risk management requirements, such as characterizing risks with quantitative risk indices or qualitative descriptors (e.g., "good" or "bad" risk). Extensions to risk evaluation may capture business impacts such as asset resilience [19]. The risk representation should be communicable to risk treatment decision-making.

The final key element, the monitoring mechanism, focuses on the decision-maker's CMS choice. CMS capabilities range from current fault detection to future condition assessment [20,21]. CMS selection involves a trade-off between a user's desire for CMS capabilities that enhance risk management and the physical or financial constraints on sensing ability. Decision-makers should evaluate CMS options before selection. The discussion above shows how CMS choice affects decisions about the other key elements and vice versa.

B. *Operations Phase*

Fig. 2-b shows the key elements during asset operations. The functional requirements of some components change between design and operations, as do some links representing an exchange of decisions and information.

The first key element, the application area, comprises an operator that overviews the asset's operation. The operator oversees the sensing and CMS setup, reviews risk evaluation and business value feedback, and implements risk treatment. In addition, the operator can analyze newly identified risk

[1] Tyrrell, Michael. Production Engineering Solutions Media. Nissan Sunderland. 2019. https://www.pesmedia.com/nissan-sunderland-new-juke-upgrading-manufacturing-final-assembly/.

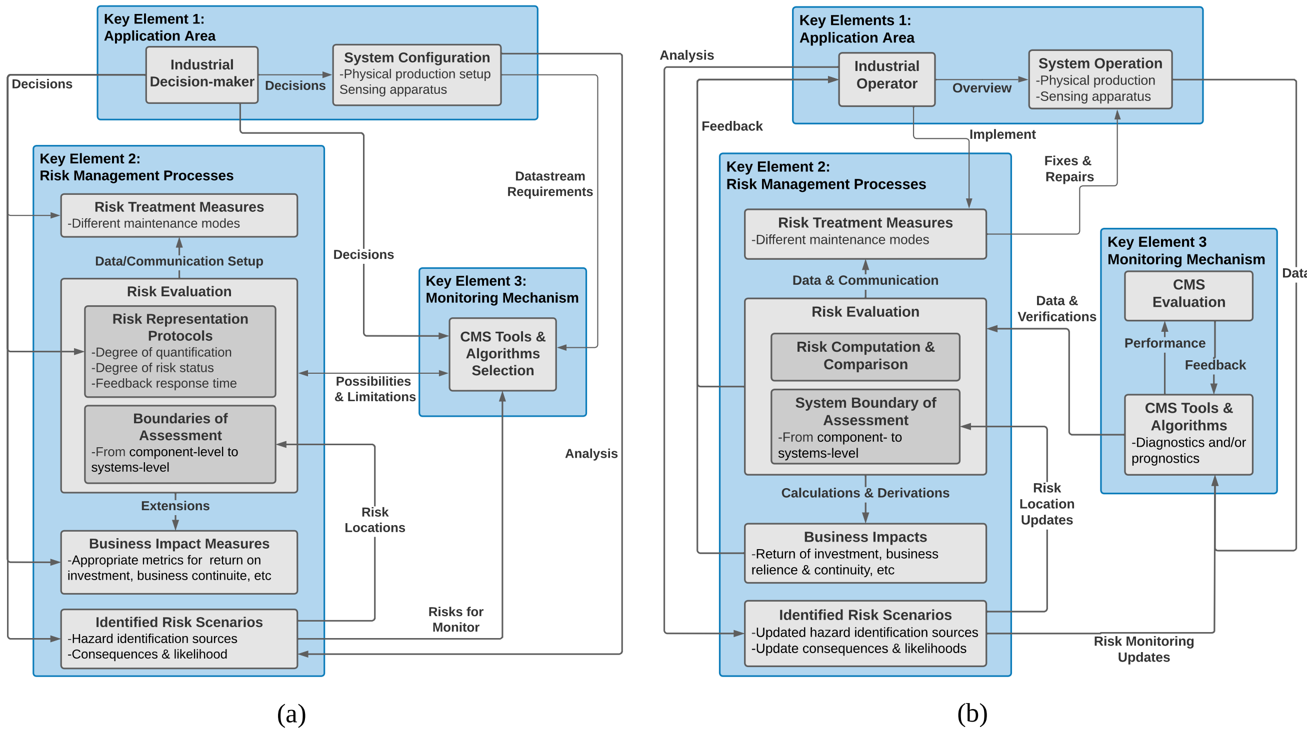

Fig. 2. A block diagram configuration of key elements, their main subcomponents, and their relationships to contextualize a CMS as part of an asset's risk management process in (1) the design phase, and (b) the operations phase.

scenarios and update the asset locations and boundaries of risks for monitoring purposes.

During operations, the second key element of risk management processes focuses on the computation and communication of data that drives risk treatment. These processes use CMS data and risk scenario analysis to evaluate risk-derived business impacts and inform maintenance of needed risk treatment (i.e., fixes and repairs). In addition, the operator can use risk evaluations to verify that the treatment measures are effective.

The CMS represents the third key element, the monitoring mechanism that drives diagnostics and prognostics. Risk analyses and asset sensor apparatus specify the data input for the CMS. Performance evaluation can accompany the CMS but should reflect the level of integration that the CMS has with asset operations and risk management. Any risk mitigation from integrating the CMS into risk management processes is indicative of the CMS's performance. However, the total capacity for risk mitigation depends on the configuration and relationships between the key elements.

IV. Evaluating Condition Monitoring Systems

Evaluation should measure the CMS's impact on risk reduction while considering its context within the three key elements. Risk-based measuring of impact compares an asset's frequency of encountered risk scenarios before and after the CMS's inclusion. However, a CMS is part of the monitoring mechanism and does not by itself reduce risk. The CMS informs risk assessment [15] and interfaces with the other key elements to reduce asset risk, so it also depends on the quality and functions of those elements in addition to its diagnostic performance. For example, a perfect CMS without risk-mitigating measures reacting to its output will have the same impact as no CMS. On the contrary, a CMS that constantly alerts for unnecessary maintenance may be worse than no CMS [4]. Therefore, any evaluation process should measure a CMS's risk-mitigating effects while examining the degree of CMS integration into an asset's risk management process during design and operations.

Understanding a CMS's context within the key elements enables constructing an evaluation process that more accurately captures CMS impact. Fig. 3 depicts the constituent processes of a conceptual CMS evaluator that can use information from the key elements, such as an asset's sensing apparatus and risk treatments. These evaluation parts include a data-generating model of the asset and its risk management, an evaluation procedure for measuring risk, asset risk scenario generation to test risk management, and a ranking of CMS options.

V. Conclusion

This study provides a basis to understand all the moving parts needed to evaluate the degree to which a CMS can enable asset risk mitigation - a task that lacks standard procedures or guidelines and is needed as closed-box-style tools become more ubiquitous for higher-stakes industrial assets. We define key elements that provide context for CMS evaluation during both asset design and operation: (1) Application area, (2) Risk management processes, and (3) Monitoring mechanisms.

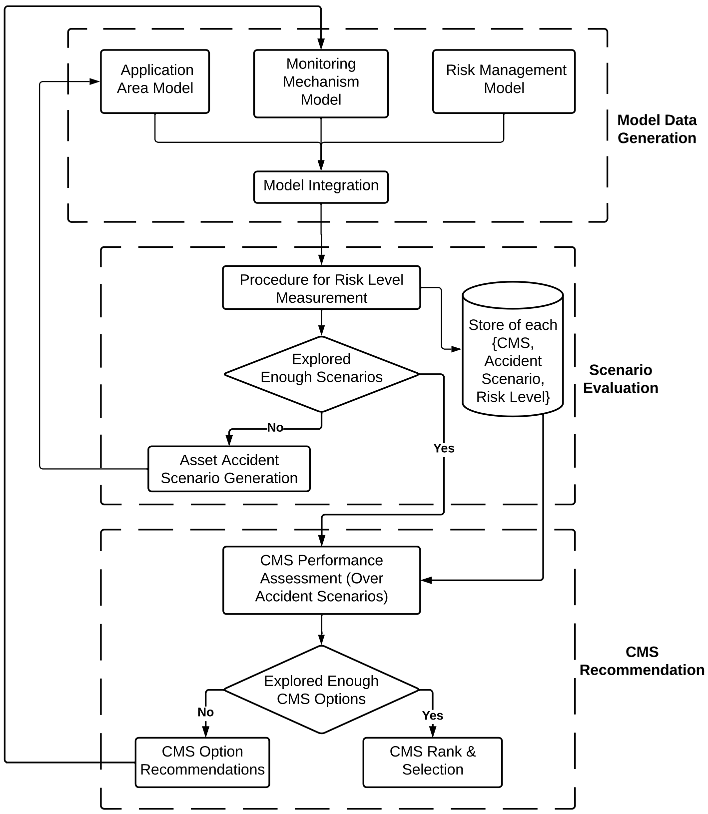

Fig. 3. Example concept evaluation process of CMS options for a target asset.

Additionally, this study provides grounds for our future exploration and design of evaluation processes and evaluators that test, compare, and recommend CMS solutions. The authors will next implement variations of the evaluation processes with simulation platforms and physical lab setups.

Disclaimer

The use of any products described in this paper does not imply recommendation or endorsement by the National Institute of Standards & Technology, nor does it imply that products are necessarily the best available for the purpose.

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