Received 19 October 2020; revised 6 December 2020; accepted 9 December 2020. Date of publication 21 December 2020; date of current version 7 January 2021. The review of this article was arranged by Associate Editor Stamatis Karnouskos.

Digital Object Identifier 10.1109/OJIES.2020.3046044

Performance Supervised Plant-Wide Process Monitoring in Industry 4.0: A Roadmap

YUCHEN JIANG [1,2] (Student Member, IEEE), SHEN YIN [3] (Senior Member, IEEE), AND OKAY KAYNAK [4,5] (Life Fellow, IEEE)

[1] Department of Control Science and Engineering, Harbin Institute of Technology, Harbin 150001, China
[2] Chair of Automatic Control Engineering, Technical University of Munich, 80333 Munich, Germany
[3] Department of Mechanical and Industrial Engineering, Faculty of Engineering, Norwegian University of Science and Technology, 7033 Trondheim, Norway
[4] Department of Electrical and Electronics Engineering, Bogazici University, Istanbul 34342, Turkey
[5] School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing 100083, China

CORRESPONDING AUTHOR: SHEN YIN (e-mail: shen.yin@ntnu.no).

ABSTRACT The intensive research and development efforts directed towards large-scale complex industrial systems in the context of Industry 4.0 indicate that safety and reliability issues pose significant challenges. During online operation, system performance degradation will lead, not only to economic losses, but also potential safety hazards. In the existing research and technical routes, the target of the fault diagnosis systems is to trigger alarms to report the fact of the existence of malfunctions as well as the underlying reasons accurately. However, it remains unanswered how urgent it is to fix it, and what degrees of fault-tolerance, maintenance, and fault recovery are needed. Further analyses are necessary to evaluate the impact of the detected fault on the plant-wide performance. In this article, to enable a more comprehensive and precise description of the plant-wide operational status, the roles of the commonly used performance metrics, the state-of-the-art performance evaluation approaches, as well as the performance-oriented and plant-wide process monitoring techniques are investigated. On this basis, an alternative straightforward technical route, embedded in the cyber-physical-social system framework is proposed. A roadmap including the key research questions, the future research directions, and an outlook about the future vision is presented.

INDEX TERMS Design technical route, distributed implementation, fault diagnosis, industrial cyber-physical system (ICPS), plant-wide process, process monitoring.

I. INTRODUCTION

Industrial cyber-physical system (ICPS) is the central research focus in the context of Industry 4.0 [1]. It aims to achieve higher control and management degree by taking into account the physical entities and the communication, control and cognition networks simultaneously. From a systems and control perspective, ICPS design involves dealing with the boosting complexity and uncertainty resulting from: (i) Stochastic and dynamic external environment in which the physical entities operate. (ii) Varying boundary conditions due to the scarcity of production capability and the shared resources. (iii) Distributed implementation on geographically dispersed infrastructure. (iv) Uncertainties from human participants, e.g., the indeterminate role of managers in sophisticated decision-making processes. At the technical level, there is a strong drive to facilitate interdisciplinary research with a special emphasis on the collaboration of the systems and control community with the ICT (information and communication technology) sector. For large-scale industrial processes, how to exploit the full capability of ICPS while ensuring the plant-wide safety and performance has attracted extensive interests from both the academia and the industry [2]–[9].

In 2016, a fascinating demonstration was given by Dr. Colin J. Parris from the GE Global Research Center to show how, with the aid of the digital twin techniques and a third-part app, a steam turbine operating at Southern California can be remotely and automatically reconfigured to avoid a potential damage to its rotor, to prolong its remaining useful life and to minimize unexpected maintenance costs [10]. However, this is still hardly realizable for the general industry today due to a lack of the connectivity in the fleets of assets as well as a constant tracking of the entire life cycle of the processes.

An uncontinuous thread makes it unconfident how a decision made to deal with one problem will affect the other subsystems and the performance of the plant-wide process. Some kind of backbone is urgently required to associate the key relevant factors for optimal trade-off.

Towards elevating the flexibility and resilience design of large-scale ICPS control and monitoring, autonomous subsystems are often incorporated in the large-scale industries. However, this leads to decentralization and the division and separation of the decision-making processes. Without effective means of supervision and control, the coordination of various functional units for the unified global targets will be impossible [11]–[13]. In this context, performance-oriented monitoring and control systems play an essential role for the top-level managers to retain the capability to promote strategic initiatives from the plant-wide perspective and to fulfill the plant-wide performance expectations.

Due to the universal existence of the broken thread in industrial practice and the introduction of autonomy, the hierarchical performance evaluation structure (both downstreaming and upstreaming) is no longer linear. The top-level management system needs to concede partial decision-making power to the lower levels where necessary local information is available and the boundary conditions are clearly defined, so that the decisions are context-aware, timely and free of transmission errors. By this means, the lower level modules of various functionalities can determine their own configurations with self-awareness. They hold the right to determine the operation modes, division of workload, scheduling, medium-term and long-term planning, etc. In the meantime, in order to retain control of the global strategies and targets, plant-wide performance indicator (PWPI) is necessary for the plant-wide monitoring tasks, the definition of which is dependent on the existing approaches for performance evaluation. It is then used for the plant-wide monitoring purpose. Based on the review of the recent progress, it is found that a majority of the design routes are following the same pattern and that data-based approaches take up a high proportion, as will be depicted in Fig. 4 (a) and discussed in Section V. These observations motivate this work, and the intended contributions include the following aspects.

- The evaluation indices of the performance of the system, the process performance metrics, the state-of-the-art performance evaluation approaches, and the key issues regarding the distributed implementation are reviewed.
- After revealing the bottleneck induced by the current research technical route, an alternative, more straightforward strategy for plant-wide process monitoring is suggested. The future vision is depicted to encourage further research efforts based on plant-wide performance degradation.
- From a broader perspective, the impact of the novel problems and techniques in the Industry 4.0 era are discussed, especially the necessity of the deeply intertwined design of the process safety and cyber-security. On this basis, a number of future research directions are recommended.

Research methodology: The sources of the referred articles include the authors' focus on the related topics as well as the dedicatedly designed searches from top-tier journals and conferences. The searching engines and the main databases used include Web of Science (Core collection), IEEE Xplore, Google, etc. The list of references is a bit IEEE-centric. The index terms include "plant-wide," "Industry 4.0," "industrial cyber-physical system," "key performance indicator," "remaining useful life," "performance degradation," "process health management," "framework" and some similar items. The year range was specified as the past ten years (2010–2020), with an intentional incline to the recent advancement over the past five years. Despite this, the most classical and influential articles/books, published even if over twenty years ago, are cited whenever necessary. Please note that this paper is not a review-type article, but more significantly oriented to the future R&D. A visionary roadmap not only needs to break through inertial thinking and possess a global perspective, but also needs to exploit the pattern in the value chain and the relationship between the stakeholders [14]. Towards this, this work investigates what prospects are expected powered by the novel research route and suggests the necessary key technologies towards such a future. This part benefits in part from the insightful articles at IEEE Future Directions (https://cmte.ieee.org/futuredirections/) and the references therein. The preliminary problems of study were initially presented at the international conference IEEE ICPS 2018 [15] and small-scale workshops/seminars focusing on plant-wide process monitoring problems.

The rest of the paper is unfolded as follows. The next section summarizes the basic problems and tasks. Towards performance evaluation system construction, Section III introduces four main evaluation indices while the approaches to calculating them are the focus of Section IV. Afterwards, Section V discusses the existing approaches to plant-wide and performance-oriented process monitoring. Section VI-A presents an alternative research route while the following subsection depicts the future vision as well as the core research directions and open research questions towards such prospect. The last section concludes the paper.

II. PROBLEM STATEMENT

The focus of this work is on the integrated design framework and the technical routes for automatic monitoring systems for safety-critical ICPS, such as process industry, intelligent factories and smart grids. Such systems are usually physically interconnected, very large in scale, geographically dispersed, and have hierarchical structures. From a macroscopic point of view, plant-wide monitoring enables global capabilities in revealing the abnormalities, coordination, management, and optimization in a reliable manner [12]. There have been emerging practical demands for various processes and plants demonstrated in the literature, including chemical reaction plants [11], [16], [17], mineral processing plant [2], Zinc hydrometallurgy plant [4], oil fractionator process [18], etc. The responsibilities of the plant-wide monitoring systems mainly include plant-wide performance evaluation, plant-wide fault diagnosis and prognosis, as well as (in the general concept) plant-wide performance optimization with maintenance.

a) Plant-wide performance evaluation: The overall performance is characterized by the PWPI, which refers to the metric of overall production and operation stability and performance, including production efficiency, total output, idle rate (scheduling efficiency), stability margin, etc. [15], [19], [20]. Please note that the concept of PWPI should be interpreted as a combination of several essential global evaluation metrics rather than an aggregated metric. One important component of PWPI is the total cost, the components of which are listed below separately.

$$\text{PWPI} = \begin{bmatrix} \text{Overall product quality} \\ \text{Total yield of the final products} \\ \text{Total cost} \\ \cdots \end{bmatrix}$$

$$\text{Total cost} = \begin{bmatrix} \text{Total energy consumption} \\ \text{Total raw material consumption} \\ \text{Equipment and depreciation expense} \\ \text{Total maintenance cost} \\ \text{Total labor cost} \\ \cdots \end{bmatrix}$$

The task is to analyze how well the plant-wide system is responding to the dynamic practical demands and dealing with numerous constraints. It will be shown in this paper that the construction of an evaluation and assessment (E&A) network constitutes a key to PWPI estimation.

b) Plant-wide fault diagnosis and prognosis: The tasks include the detection, localization, identification, and prognosis of faults with special focuses on hierarchical, distributed, decentralized, and networked system configurations.

- *Fault detection:* To answer the question of whether or not the system is operating in a healthy status [21].
- *Fault localization:* To determine the subsystems, the devices, and the components where faults occur; To determine the source (the origin) that induces other faults [22].
- *Fault analysis:* To provide more in-depth information after fault detection; To examine the reason and the root cause that lead to the faults, and the impacts through propagation [23]; To determine on which level should fault tolerance and maintenance be carried out [24].
- *Fault prognosis:* To infer the failure of the machines/ the malfunction in the process online, and predict them before actually taking place [25].

In addition to the above tasks, it remains unsolved how to gather contextual (only the required and the transmissible) real-time data and operation status information from different functional units; how to determine the degree of emergency of different faults; and how to distinguish faults from malicious external attacks.

c) Plant-wide performance optimization with maintenance: Conventionally, optimization, and maintenance are usually classified as system synthesis tasks rather than analysis tasks [2]. In the plant-wide performance supervised design problem, they are too intertwined to be separately studied.

- *Fault tolerance:* To suppress the fault-induced influences *temporarily*, by taking actions to retain the overall stability and key performances [5].
- *System recovery:* To carry out maintenance procedures to eliminate hardware failures and process malfunctions for healthy status with long-term reliability [22].
- *Optimization:* In terms of a specific period of time, to achieve predictive scheduling that improves the overall adaptiveness to the dynamic external factors and PWPI by adjusting the organization of the functional units [2].

From the perspective of system analysis, nominal PWPI can be derived when the nominal local performance indices are defined and the scheduling rules of the available resources are specified. In contrast, plant-wide optimization is a completely reverse process [2]. According to the upper-level commands, the scheduling unit determines nominal PWPI, denoted by $Q_{pw}(k)$. From the top-down, an "allocator" $f_i(\cdot)$ is determined such that $Q_i(k) = f_i(Q_{pw}(k))$ where $Q_i(k)$ denotes the unit operational indices of subsystem i from time k till the next update. Furthermore, the set-points in each subsystem are determined according to $Q_i(k)$. In the multi-level structure, the procedure is repeated by analogy. It should be noted that in practical applications, the design of $f_i(\cdot)$ is subject to the feasibility and equilibrium requirements, as well as the numerous constraints from the subordinate units.

In large-scale industrial enterprises, the operation core conducts most of the activities that are directly related to production [2]. It is composed of the largest scale of production-related physical entities, and there normally exists redundant productive power applicable to a wide range of production demands, e.g., machines with functionalities that are mutually replaceable. According to certain grouping criteria, key performance indicator (KPI) management systems are designed corresponding to each group, and on this basis, they are assigned temporal goals.

For those production tasks involving evident sequential and temporal dependences, such as the sub-processes on the same production line, the successful operation relies on the simultaneous functioning of different units, which are respectively responsible for unique tasks. Each unit has time-sensitive goals to achieve, typically characterized by the desired outputs. If a unit fails to fulfill certain goals, its downstream sub-processes will be affected. In the worst case, the influence will propagate in a chain reaction and lead to cascading effects causing performance degradation of the overall process. By mathematical formulation, a fault in *Unit i* will affect the performance indicator of *Unit i* as well as the downstream of *Unit i*:

$$\Delta Q_{pw} = f(\Delta Q_i, \{\Delta Q_j | j \in \mathcal{D}_i\})$$

where ΔQ_{pw} denotes PWPI degradation, ΔQ_i and ΔQ_j respectively denote the performance indicator degradation of

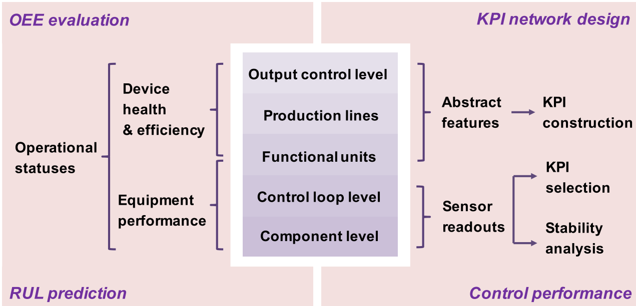

FIGURE 1. **Descriptors of process performance.**

Unit i and j. $\mathcal{D}_i$ is the set of all downstream nodes of *Unit* i. It should be noted that some faults will stop propagation due to the protection mechanisms of the devices/units [26].

III. PERFORMANCE EVALUATION INDICES

Before reviewing the recent progress in the approaches for performance evaluation, the descriptors that quantify the performance of the industrial systems are summarized. As shown in Fig. 1, key performance indicator (KPI), remaining useful life (RUL), overall equipment effectiveness (OEE) and control performance indicator (CPI) constitute the main evaluators, oriented to different aspects of the overall system.

A. KEY PERFORMANCE INDICATOR NETWORK

Key performance indicator (KPI) is an extensively used terminology by the human resources sector to evaluates the performance of staff [27]. This concept is introduced to the industrial monitoring and management field to characterize the variables that play dominant roles in the overall production process. For practical applications, KPIs need to be designed to reflect the operational status of the core functional units, and based on this, to reveal and forecast the variations in the multi-dimensional performance requirements, such as the economic expectations and the health status of the life cycle management (LCM). However, most of the related literature assume the existence of well-designed KPIs, their focus being mostly on proposing KPI prediction approaches and KPI-oriented process monitoring schemes [28]. Furthermore, compared with the conventional monitoring tasks, the concept of the KPI-oriented process monitoring does not have a long history [29]. Based on these considerations, how to design the KPIs appropriately in large-scale distributed and hierarchical systems and to make full use of the potentials of KPIs requires more attention in future research [23].

There are three major issues to be emphasized to exploit the greater potential of KPI-oriented plant-wide process monitoring. First, the concept of "KPI network" is introduced to the hierarchical system structure [24]. KPIs are designed at each level to quantify the behaviors of the production processes while having dependency with the upstream, the downstream, and the parallel KPIs. On top of the physical connections, the communication networks, and the control networks, the KPI network constitutes an essential auxiliary structure, established in the virtual space for the networked monitoring systems. With the KPI network, fault localization and tracing become more straightforward, and it lays the necessary foundations for KPI-oriented plant-wide optimization.

Second, although KPIs can be calculated based on practical production data, how to specify desired values in the control tasks is still subjective. This drawback can be eased with the correlations embedded in the KPI network. Nevertheless, the monitoring system designers and analysts need to bear in mind that the KPI network may *NOT* contain all information required for fault diagnosis due to the inevitably unmodeled factors: some expert knowledge is too complicated to be quantified while some other dominant factors are unnoticed and therefore omitted. This leads to an asymmetrical network configuration for the bottom-up integration and the top-down allocation/tracing tasks. On the other hand, when specifying the desired KPIs, which involves dynamic adjustments according to multiple time scale (short-term/long-term) planning and strategic arrangement, boundary conditions such as the maximum input-output ratio, available productive forces, inventory, and even the external impacts must be taken into consideration.

Third, network topology changes induced by the structural reform do not necessarily indicate redesigning the KPI network starting from scratch, especially when the variations are simple (e.g., addition, subtraction, or reorganization of parallel/replaceable functional units) or sequentially separable (e.g., incorporating adjacent links in the industrial chain). Dynamic KPI network configuration is also applicable for temporarily Adhoc scheduling purposes. Furthermore, for dynamic processes, it is favorable to switch the KPI network configurations at different LCM stages to incline to the current goals.

B. REMAINING USEFUL LIFE

Remaining useful life (RUL) is another evaluation index that attracts extensive research interests in the modern industry. As one of the central tasks of the prognostic and health management (PHM) system, existing RUL prediction approaches are mainly based on the expert knowledge and mechanism models established with the aid of colossal amounts of historical data [30], [31]. The prediction results will be further used to adjust the maintenance schedule and be used for the recovery of performance degradation. Compared with other performance indices, RUL prediction is designed to be reliable-critical, to reflect the worst-case, and to generate the deterioration trajectories along time, which are supposed to be monotonically decreasing.

Unlike KPI that can be calculated based on the data from the current or a past period of time, RUL is future-oriented, and the prediction values may deviate from the true situations due to complicated reasons. Both the accessibility of the training data and the degradation model to be adopted have much impact on the credibility of the prediction results.

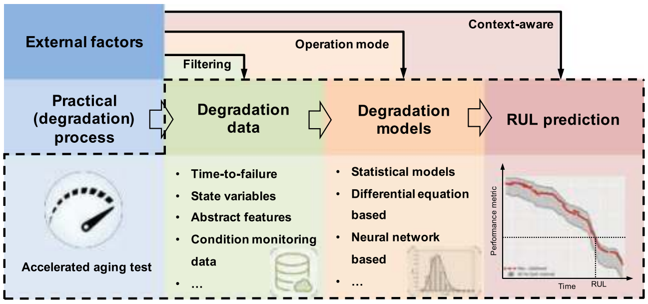

FIGURE 2. **Obtaining RUL predictions: how to be more reliable.**

Fig. 2 illustrates the general design procedures for predicting the RUL. In the scenarios where historical degradation data are unavailable, accelerated aging tests (or accelerated failure tests) are designed to compress the degradation process to an acceptable time-scale in the form of repeatable and consumable experiments to duplicate the practical evolution processes. During the tests, characteristic variables, such as those listed in Fig. 2 are monitored. They are recorded to construct databases that cover multiple operation modes and failure modes. With the informative database, various types of (mixture) prediction models can be constructed. To improve accuracy, it is favorable to develop context-aware approaches that take into consideration the working conditions to suppress the influences of external factors.

C. OVERALL EQUIPMENT EFFECTIVENESS

In the fields of the manufacturing industry and some process industry, overall equipment effectiveness (OEE) is a popular evaluator. It synthesizes the factors that cause productivity loss in three major aspects: availability, efficiency, and quality.

Availability characterizes the time utilization ratio, i.e., the operation time/shutdown time of the production line, which could be affected by both the scheduling performance (planned downtime) and the process faults (unplanned downtime). To reduce the planned downtime, dynamic/real-time optimal scheduling approaches that are robust to constraint variations, internal failures, and external changes are needed. To reduce the unplanned downtime, small-delay fault diagnosis systems and intelligent decision modules that can achieve prompt failure recovery maintenance strategies are needed.

Efficiency is also called performance or capacity utilization ratio (as in Wikipedia). It measures the relative speed the machinery is running at with respect to the full speed or the rated maximum power. In industrial practice, high efficiency is achieved by reducing the idling time and setting high operation speed. However, such high demand will lead to serious depreciation and a decline in the yield rate.

The third factor, quality, characterizes how well the products meet the standards. For most applications, quality indicators are generally not calculated online but calculated when a batch of production outcomes are available or when the final products are fully analyzed. This will introduce much delay before the performance is degraded to an unacceptable degree, during which time the system is still operating and generating products with major defects. As a result, how to reliably predict the quality of final products has become a hot research topic in recent years.

D. CONTROL PERFORMANCE INDICATORS

In the control layer, control performance assessment has distinct means and standards [32]–[36]. The process variance (output variance) index and user-specified performance specifications can be adopted for control loop performance evaluation. Some key factors to characterize the coherence of control performance include pole location, upper bound of the variable variances/covariances, peak amplitude, entropy, and the stability margin (maximum amplification effect) of the system [37]–[39]. In the well-developed theory of optimal control, the optimity of several simple types of system (such as linear time-invariant system, affine nonlinear system, and double integral system) has been solved, in which the constraints (boundary conditions) are addressed in the cost function to deal with the problems of time/control input/energy consumption minimization [40]. As special KPIs in the control layer, they are referred to as control performance indicators (CPIs). It should be noted that it is more favorable to carry out evaluations based only on the routine operating data rather than performing additional tests on the system. From a frequency domain perspective, power spectra analysis can be employed to reveal periodical characteristics for energy systems such as smart grids. Compared with time-domain indicators, it is easier to deal with data defects and network induced time delay [25], [37].

IV. PERFORMANCE EVALUATION APPROACHES

A. KPI PREDICTION APPROACHES

Conventional KPI prediction schemes are dedicated to revealing the dependency between process measurements and KPIs [41]. This requires plenty of underlying mechanisms and expert knowledge as the fundamental to derive the quantitative equations. However, the modeling processes are hardly achievable for large-scale complex systems and therefore sometimes unsuitable for plant-wide monitoring tasks.

In recent years, approaches based on multivariate statistical analysis (MVA) have gained more popularity for plant-wide system monitoring due to their capability to make use of the correlation among process variables [42]. It should be noted that for the prediction problem, correlation analysis does not need a rigorous reasoning process and an interpretation of the internal principles. The construction of the correlation relationship is straightforward, as long as proper training data are available. A comprehensive review is presented in [25]. In parallel, there is also an emerging trend towards KPI prediction based on learning techniques [28], [43], [44].

In another aspect, data-induced challenges are being solved with newly proposed approaches. In terms of compromised data quality, abnormal sensor readouts identified as outliers are dealt with in [45], and contaminated measurements are cleaned in [46] and [47], Regarding data availability, packet loss and multiple sampling rates related issues have been taken into consideration [45], [48]. In addition, research towards reducing data safety risks such as malicious false data injection attack is in progress [49].

In a plant-wide system, "the curse of dimensionality" becomes evident due to the boosting amounts of data [50]. In this context, variable selection, feature extraction, and feature elimination (dimensionality reduction) play an important role. They have been studied extensively over the past few decades [51]–[53]. Fruitful results have been reported with successful applications to almost all domains of natural science and social science such as disease diagnosis, business analysis, and market forecasting, etc. With the support of transdisciplinary collaboration, many of the approaches can be redesigned to be applicable for engineering purposes. For instance, as a part of the plant-wide monitoring tasks, digital signal processing, image processing, and data mining generally involve preprocessing procedures to obtain structured and pre-filtered databases with carefully selected variables [54]. Apart from the variables directly defined based on measurable physical quantities, abstract features are also constructed with machine learning techniques and multivariate analysis to characterize dominant properties of systems or processes [55]–[58]. The interested readers are recommended to explore more in the review article [50] and the references therein.

B. RUL ESTIMATION APPROACHES

Regarding the availability of degradation data, the main sources for large-scale processes include historical databases and event logs while the device level and component level data are mostly generated in the laboratories dedicated to the construction of aging models. To mitigate the problem of insufficient performance degradation data, further research efforts are required towards four strategies: (i) accelerated aging test [59], (ii) hardware-in-the-loop (HITL) simulation [60], (iii) semi-supervised online learning [60], and (iv) developing digital twins tools [61]. Generally speaking, the former two strategies need destructive tests while the latter two tend to be non-destructive.

Regarding model construction, there are various types of models proposed to characterize the performance degradation processes. For instance, first principle-based (Coffin-Manson model [62]), learning-based (deep neural network [63], sparse auto-encoder [64], extreme learning machine (ELM) [65]), algebraic equation-based (linear regression with constraints [66]), differential equation-based (Kalman filter [67]), statistical hypothesis based (Gaussian process [68], Wiener process [69], particle filtering [70]), signal processing based ([71], [72]), etc. As for model selection, a degradation model is appropriate only if the type and characteristics of the system/process are taken into careful consideration, for instance, the system dynamics, nonlinearity, parameter variation, etc. Besides, the availability of the training data and the potential identification methods should also be considered.

At the last stage of design (Refer to Fig. 2), most of the existing performance degradation-based approaches define RUL as the length of time before the performance curve hits a threshold [73]. The determination of the threshold has a significant impact on the estimation result, especially when the performance decline rate is low. Common solutions to threshold selection/calculation can be summarized in three categories: (i) expert knowledge-based (e.g., [64], [70], [74]), (ii) statistical hypothesis-based ([69], [75]), and (iii) experimental/manual setting ([76]–[78]). Alternatively, based on the concept of the health/degradation state, RUL can be defined as the expected time before maximum separability between different states is found [77]. It is interesting to find that following this definition, RUL estimation can be analogized as the LCM of the health index signals. The design tasks include identifying finite health/degradation states, calculating the probability mass function of the health states, as well as constructing the maximum likelihood state estimator and RUL predictor.

Apart from algorithmic innovations for general applications, a large proportion of research outcomes also focuses on the RUL prediction of specific components or devices, for instance, power transformers and transducers [71], [75], [79]; supercapacitors [78], [80]; transistors (MOSFET, IGBT) and diodes [62], [70], [81]; bearings [66], [67], etc. Other previous review can be found in [82], [83], [60], [84], [77] and the references therein. Furthermore, the definitions of the related terminologies and the role of RUL in the prognosis and health management framework can be learned from [85].

C. CALCULATION OF OEE AND CPI

As widely adopted, OEE is calculated by $Availability \times Efficiency \times Quality$. The evaluation of OEE is rather straightforward because the calculation is heavily dependent on how the three-tuple (availability, efficiency, quality) is quantified, and is more related to the definition of how close a device is operating compared with the full potential (the nominal specifications).

As for the evaluation of the CPIs, there have been fruitful traditional techniques for the offline analysis, many of which have been extensively studied and included in the textbooks [86], such as the root locus technique in the time domain analysis, and the frequency response techniques, e.g., the Bode plot and the Nyquist plot. Nevertheless, it is practically demanded to design online evaluation approaches, especially those oriented to the quantification of the robustness of the closed-loop systems.

In the past decade, both model-based and data-driven approaches have been studied. In [39], a multi-objective constrained close-loop control assessment approach was proposed for a user-specified benchmark. Constraints are formulated as linear matrix inequalities (LMIs), and the multi-objective optimization problem is converted to the concave minimization problem subject to the corresponding LMI constraints, which is solved by a cone complementarity linearization algorithm. Based only on streams of process data and without the need for the plant model, a fuzzy performance index is defined to assess the control loop performance in [37]. The core idea is to calculate the coherence degree between the signals with the aid of the operation state classification. More recently, a data-driven computation approach of the gap metric and the optimal stability margin is proposed in [38]. The gap metric characterizes the distance between the subspaces in the Hilbert space, and the stability margin characterizes the maximum tolerable uncertainty of a closed-loop system before unstable.

V. PLANT-WIDE PERFORMANCE ORIENTED FAULT DIAGNOSIS

A. REMARK ON THE CONCEPTS

Since performance-oriented fault diagnosis is only half step away from performance optimization, some concepts have to be clarified first, before diving into discussions about concrete ideas and solutions. Specifically, at the top-level of the plant-wide system, the difference between strategic decision-making and performance optimization is clarified.

A good decision requires visionary planning. This means that the decision-makers must base on the full understanding of the current situation and the future trend from a global perspective, and need to coordinate the power in the plant-wide system with a trade-off between the contradictory factors in an indeterministic situation. Sustainable development outweighs stage optimality. For this purpose, good risk control, adaptivity, and robust capital chain are considered on top of achieving maximized profits.

By contrast, an optimal performance indicates that the key factors have been addressed well in terms of the specific operational condition and the specific working context that have already or will have taken place. In this sense, it is evaluated based on the deterministic facts of the current or a past period of time. Its target lies in completing specific tasks, whose results can be expected, and meeting the highest expectations. Nevertheless, when a top-level decision has been made, plant-wide optimization can be pursued.

B. EXISTING APPROACHES

Despite that the research towards performance supervised plant-wide process monitoring is still in the infancy stage, performance-oriented fault detection and plant-wide monitoring in the general sense have received plenty of efforts in recent years. This part investigates the recent progress from several aspects.

In terms of the division of a large-scale system, multiblock MVA based approaches were proposed in [16], [17], [26], [87], most of which fall in the distributed modeling framework proposed in [11] or the data-driven distributed monitoring framework proposed in [12]. Facing the challenging task, the plant-wide process decomposition procedure in these works still requires *a priori* knowledge and might remain a bit arbitrary. All testified on the Tennessee Eastman process, the work [11] relied on the process knowledge and constructed 3 sub-blocks; the work [26] referred to the information resolution capability of principal components and constructed 15 sub-blocks; the solution in [16] was based on the functional unit and constructed 4 sub-blocks while a different set of 4 sub-blocks was adopted in [17].

In terms of local monitoring, the fault detection task has been well addressed. Multiblock principal component analysis (PCA), multiblock partial least squares (PLS), hierarchical PCA/PLS, localized Fisher discriminant analysis, as well as many other generalized MVA models and their nonlinear extensions (e.g., based on the kernel technique) provide great foundations for the distributed or the decentralized implementation of the local detectors [88].

Regarding fault localization, a successful application can be found in [17]. The indicators of faulty sub-block and faulty variable were derived based on the alarm counts and reconstruction-based contribution for rough localization and precise localization, respectively [89]. For root cause analysis, authors in [23] proposed a tensor subspace analysis-based discriminant analysis approach in case of multiple faults. As for the approaches where each sub-block contains partial information of the complete set of process variables, such as in [26], common responsible variables can be regarded as the suspects of the root cause of faults.

Oriented to the plant-wide performance, the recent progress in the fault diagnosis and prognosis approaches was illustrated in [25] with an open-source Matlab toolbox. Recently, the authors of [23] proposed to use a modified canonical variable analysis (CVA) approach that can distinguish KPI-related and unrelated subspaces at both the plant-wide level and the sub-process level. For better reliability, how to combine/synthesis parallel algorithms with available process knowledge was studied in [36]. An attempt was made for control performance diagnosis with discrete monitoring outputs using Bayesian inference. From the communication point of view, some perspectives on the integration of the data-driven and event-driven processes were presented in [90], which addresses the challenges in deployments.

In a plant-wide system, while many of the subunits can be regarded as operating under static conditions, this is not often the case at the lower control loop level. For instance, batch processes are composed of at least two operation phases and the transient phase does not satisfy the stationary assumptions, i.e., the mean values of the variables and the variances are not constants. For customer-oriented production lines, the set-points of closed-loop control systems change according to the specific requirements (various expected values). Moreover, there are circumstances when the variation of the working condition cannot be neglected, for instance, the temperature changes due to seasonal changes. There is an urgent need to deal with the strong dynamics as well as the operating mode-dependent and non-stationary processes, especially in the plant-wide systems where multiple of the above-mentioned scenarios can simultaneously take place. If the complete system dynamics are known, a scalable plug-and-play (PnP) approach to distributed fault detection is

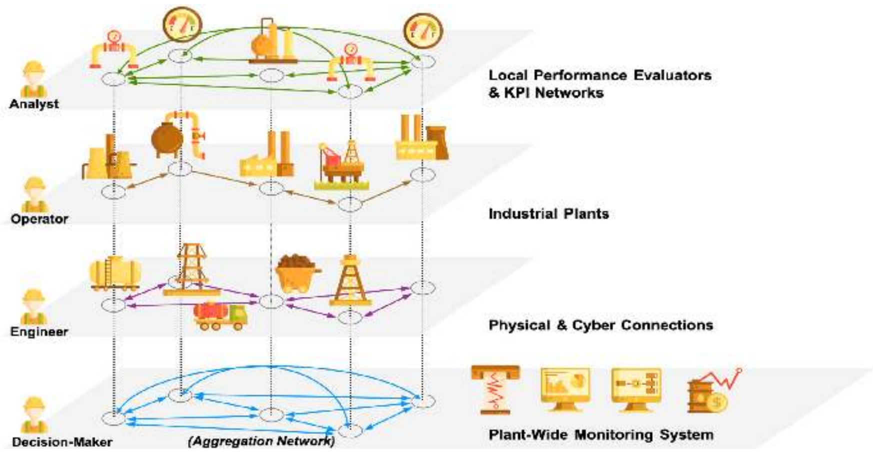

FIGURE 3. Distributed performance supervised plant-wide monitoring system: From the CPSS perspective.

available for interconnected large-scale systems [91]. In [92], sparse cointegration analysis was adopted to distinguish the static and dynamic equilibrium relations in the closed-loop configuration. In addition to the static equilibrium errors, it was proposed to simultaneously monitor the temporal equilibrium errors, enabling the MVA based approach to make use of the process dynamics.

In the next subsection, more discussions about the distributed implementation of the monitoring systems and the overall decision-making mechanisms based on local information fusion are presented.

C. DISTRIBUTED IMPLEMENTATION

1) DISTRIBUTED MONITORING CENTERS

A distributed system can be modeled by a set of fully-interconnected subsystems or interaction-oriented subsystems [93]. As for the former representation, the dynamics and outputs of the subsystems are driven by their states, the control inputs, and the external states. For the latter representation, the subsystem dynamics is driven by its states, the control inputs, and the received information from the neighbor nodes. Generally, the received information is denoted by the weighted sum of all the sent information from the other subsystems.

Assume that the plant-wide process is composed of a group of subsystems. Each subsystem is correlated to the neighboring subsystems through the cross-states and the communication channels. Meanwhile, there are several geographically distributed monitoring centers constructed, jointly responsible for the plant-wide monitoring task. As shown in Fig. 3, the subsystems are represented with nodes in the network, and the corresponding process information is sent to one adjacent monitoring center for local fault diagnosis and fault localization. The distributed implementation of the plant-wide monitoring system task is to develop local monitoring systems sensitive to plant-wide performance degradation at each monitoring center, using only the local process data and the communication information with the adjacent nodes. The interested readers are referred to [93].

Each distributed monitoring center plays several roles:

i) *Master node:* From the perspective of hierarchical management, each monitoring center is a master node. By contrast, the subunits within the jurisdiction can be regarded as slave nodes which are liable to the monitoring center and upload the status and data only to the corresponding master node. In another aspect, the local monitoring center is responsible for revealing plant-wide performance degradation and potential faults, through communication with other master nodes in the network.

ii) *Datacenter:* To collect, store, and dispatch the process data in charge. The data center also maintains a local historical database.

iii) *Computing center:* To perform large-scale neural/matrix computations online in real-time to serve the local fault diagnosis systems and process other computation related requests.

iv) *Problem solver:* At both the software and hardware levels, to identify the sources that cause major performance degradation and isolate the faults. After the failure recovery procedures, a re-evaluation will be carried out.

v) *Resource allocator:* Having gathered all the real-time operation status information, the local monitoring center aids to schedule the sub-process and the devices in terms of vacancy, health status, efficiency, etc.

2) FUSION OF RESULTS FROM THE NODES

In this part, the extensively studied fusion approaches are reviewed.

i) *Weighed statistics based fusion strategy:* The underlying idea was originally used in the locality learning problems and the nonlinear approximation problems [94], [95]. The weight is determined by a metric, characterizing how far an observation deviates from the local data origin, i.e., the distance between data [38], [96]. However, in the fusion task of the distributed implemented test statistics, it should be noted that there is a major difference: each node has its own dynamics and specifications. Recall that the weights should reflect the contribution of each node to the overall system, in the fusion problem, a metric can be adopted only if it characterizes the degree to which each subsystem deviates from the normal working condition. In other words, the distances between the nominal systems and the actual systems should be quantified and measured online. Following this, the fused evaluation index and the fused threshold can be respectively defined as the weighted sums of the local evaluation indices and the local thresholds, where the weights are defined as the distance metric.

ii) *Probability theory-based fusion strategy:* Assume that the local null hypothesis denotes the degradation-free or fault-free condition at each node, and the local alternative hypothesis indicates performance degradation or faulty condition at each node. On this basis, the total null hypothesis is defined as the simultaneous satisfaction of all the local null hypothesis, and the total alternative hypothesis is the opposite hypothesis of such.

Considering that the nodes are not mutually independent, the probability of accepting the total null hypothesis under the condition that all the observations happen cannot be directly calculated by the multiplication of the local probabilities. To deal with this, the core idea is to use the Bayesian formula and the total probability formula to solve for the posterior probability by using the priori probability. The unconditioned probabilities of whether a fault occurs or not can be assigned a preset confidence level and the corresponding significance level, respectively. The calculation of the priori probability can be referred to [11] and [92].

iii) *Voting based fusion strategy:* Similar to the organizational decision-making schemes, each local center is assigned a binary "YES/NO" vote. From the plant-wide perspective, the degree of trust of each node, which is usually a pre-defined function of the local historical false alarm rate and the local missing detection rate, plays a significant role in such a strategy.

VI. ROADMAP FOR PLANT-WIDE MONITORING IN THE INDUSTRY 4.0 ERA

A. ALTERNATIVE RESEARCH ROUTE

The existing literature describes efforts mainly in decomposing the plant-wide process into smaller-scale ones. In nature, these approaches are dedicated to degenerating the plant-wide problem into a local monitoring problem. As shown in Fig. 4 (a), this technical route mainly involves answering three questions: (i) how to automatically group the set of all available process variables collected from the plant-wide system into sub-blocks based on abstract features [26]; (ii) how to design local monitoring systems; and (iii) how to combine local results for global decision-making [11]. Nevertheless, additional efforts are needed for explicitly tracking and localizing the faults (inversely from global to local). In today's engineering practice, almost all fault diagnosis systems are designed locally inside some functional units without considering the interactions between the units. Generally, they treat external

FIGURE 4. Comparison of two technical routes.

factors as unmodeled uncertainties or disturbances. In a recent article [91], approaches have been proposed dedicated to a better use of the information about these interactions.

This paper emphasizes that the design of the plant-wide monitoring system needs to take into consideration the existing organizational structure, the operating mode, the strategies and aims of the plant-wide system, and even the human and social factors. These objective facts also need to be treated as design inputs as a part of system knowledge. Otherwise, the difficulties in interpreting the fault mechanisms will be hardly surmountable. It should be noted that a plant-wide process does not necessarily indicate a fully automated process. This is a common misunderstanding or illusion of thinking regarding plant-wide performance supervised design. With human operators involved in the interval of sub-processes, some necessary information and data during the consecutive operation are intercepted. In this context, while some operations can be evaluated with quantified standards, the others can be only supervised using obscure indices.

An alternative more straightforward research route for plant-wide performance supervision and optimization shall be in the cyber-physical-social system (CPSS) design framework (refer to Fig. 3). The design technical route for performance supervised plant-wide monitoring mainly includes two parts: performance evaluation system construction, and performance-oriented fault diagnosis approach development, as shown in Fig. 4 (b).

In the conventional sense, the target of the fault diagnosis systems is to *accurately* trigger alarms in case any malfunction happens. The "accuracy" here can be interpreted as an optimal fault detection rate with effectively suppressed false alarms. In other words, the target is to report the fact of the existence of malfunctions as well as the underlying reasons accurately. However, it remains unanswered how urgent it is to fix it, and what degrees of fault-tolerance, maintenance, and fault recovery are needed. Further analyses are necessary to evaluate the impact of the detected fault on the overall performance. Specifically, performance degradation of all related subsystems needs to be estimated with the aid of fault propagation analysis, which is a quite challenging task. What we intend to emphasize is that the design paradigm of separating the fault detection process and the fault analysis process may lead to unnecessary workload to the design of plant-wide performance supervised process monitoring system. Thereby, the more straightforward strategy for plant-wide process monitoring is to design fault diagnosis systems that only trigger alarms when the PWPI has deteriorated.

In simple scenarios, the direct relationship between the PWPI and the operation status of each subsystem (via the KPI network) can be established. Performance supervised analysis and optimization of PWPI can be performed, using either deductive or reasoning methods. No extra analysis is needed. However, this is sometimes hardly achievable due to the complexity of the fault propagation mechanism, induced by the interconnected subsystems. A reasonable relaxation of "establishing a direct relationship" lies in designing fault diagnosis systems with the aid of the calculated PWPI so that they trigger alarms only when the faults have a high likelihood to result in severe degradation in PWPI, rather than conventionally trigger alarms whenever a fault is detected regardless of its amplitude and impact to the other parts of the plants.

Playing an essential role in the next generation smart factory, plant-wide process monitoring helps to elevate the operational transparency and therefore lays great foundations in forming a close-loop with the decision-making and the optimization of industrial processes. However, in terms of the emerging large-scale processes that are composed of plenty of production lines, devices, and tens of thousands of components, it is neither possible nor economical to maintain every single item and fix all the malfunctions in time—this greatly weakens the value of the obtained results. In this sense, performance supervised plant-wide process monitoring can reveal the degradation in the dominant factors that are directly linked to the high-level scheduling and decision-making tasks, and beyond this, will contribute to the integration of the upstream and the downstream industry chains and value chains, even promoting new services. In the existing roadmap article [97], study towards the real-time monitoring of PWPI is listed as the top recommendation to enable the next generation of the manufacturing industry.

B. FUTURE VISION AND RESEARCH DIRECTIONS

Technology advancement is the enabler of novel products and services. What drive the inevitable evolution are the added values and the benefits brought to the customers (the market). The following part presents what to expect in the next decade powered by the proposed research route, and on this basis, suggests the necessary key technologies towards such a future from a multidisciplinary view.

Fig. 5 shows the milestone technologies to achieve for the transformation from the traditional process monitoring practice to the performance supervised plant-wide monitoring. Today, the industry is rapidly adopting them, and the internal processes and the whole value chain are being reshaped [98]. In the dimension of platform and infrastructure, core aspects include the construction of information containers, distributed monitoring networks, protocols and standards, as well as the realization of the digital twins of the plants and services. In the dimension of algorithmic improvement, the fuel to drive

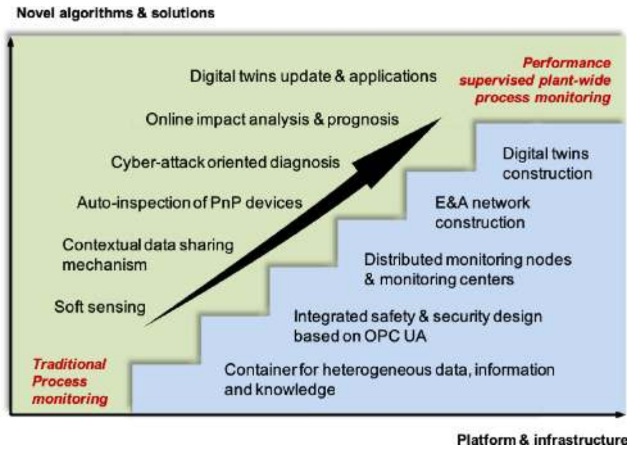

FIGURE 5. Roadmap to performance supervised plant-wide monitoring.

the E&A network lies in semantic perception (soft sensing & contextual data learning). The functioning of the critical safety and security infrastructure in an autonomous manner is achieved by automatic configuration/inspection of the PnP devices and the online analysis and prognosis of the impact caused by internal faults or external attacks. Meanwhile, the development of digital twin (DT) based services such as full life-cycle tracking will act as an indispensable part of the novel paradigm due to the benefits for system transparency and accessibility from a global perspective. The top-priority research directions and open questions are summarized in Fig. 6. They will be explained in detail in the following subsections.

1) FULL-SCALE OPERATIONAL AND MAINTENANCE TRANSPARENCY SUPPORTED BY THE EVALUATION & ASSESSMENT NETWORK

In the conventional monitoring schemes for large-scale systems with hierarchical structures, cross-level information is usually intentionally ignored and left out from the information flow due to a lack of formal message broadcasting mechanisms. By constructing the E&A network, it provides a novel topology for transparent information flow of the performance degradations and other relevant data. For the high-level supervisors, this is a key to promptly localize the problematic subsystem after a malfunction is detected. Assessment is meaningful because it helps to monitor the reliability and trustworthiness of the sub-processes that the corresponding human participants are in charge of. In this sense, the most relevant "social" factor (i.e., the first S in CPSS) can be effectively included in the online close-loop.

In the physical space, the properly-structured infrastructure set constitutes a dedicated transmission network for the heterogeneous data generated by different devices and establishes an efficient transmission route across the levels. In the unified framework, the synchronization techniques can play a better role in dealing with the inconsistent time-delays, and the data association techniques can better help to generate

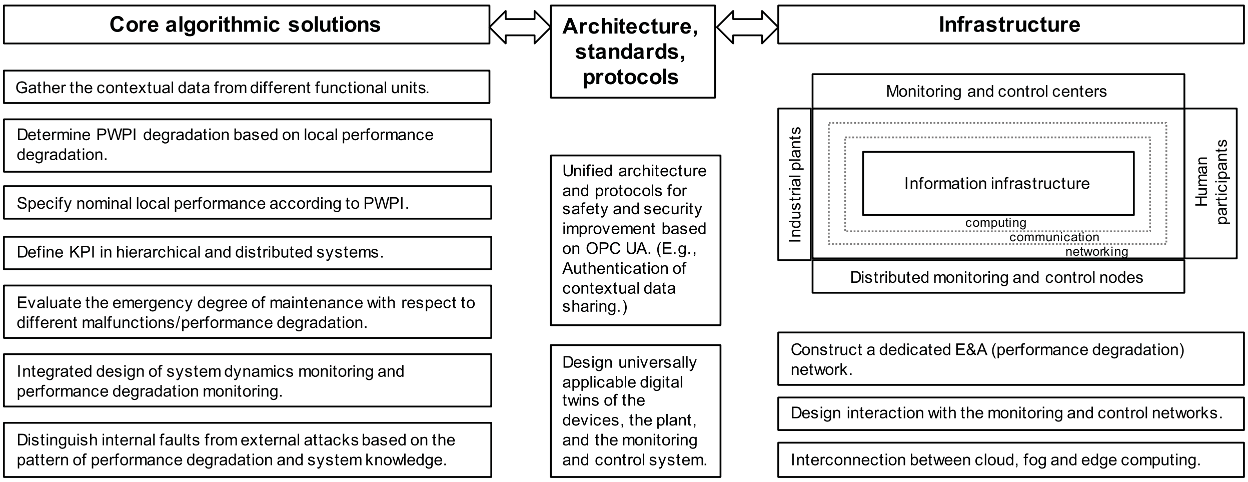

FIGURE 6. Summary of top-priority research directions and open questions.

semantic data. As a result, this will facilitate the control and management center to give time-sensitive instructions.

2) ACTIVE COMPENSATION OF THE SAFETY DEFECTS INDUCED BY THE SECURITY BREACHES

The openness of the system is one of the key factors to exploit the best potentials of ICPS. In addition to an increase in the plug-and-play devices deployed at the production end, there is an emerging trend in enhancing the connectivity between the production-end and the business end. As a result, physically-isolated industrial control networks become exposed to external attacks. Once the security line of defense falls, the safety of the production sites will be straightforwardly threatened.

Despite that the security issues of the networked systems have raised extensive attention in the post-Snowden age, plenty of the existing industrial processes was not initially designed with such consideration, which provides possibilities for the malicious attackers to make use of the defects to carry out illegal activities such as eavesdropping and launching integrity attacks. Compared with IT attacks, the cyber-physical attacks to the process control systems cause physical damages. Several world-shocking events have taken place, such as the infamous Stuxnet virus and the intrusion events of the German steel mill, the Ukraine power grid, and the Iran nuclear power plant [99], [100]. Having been aware of the possibility of cyber-physical attacks, the performance supervised plant-wide monitoring system can reveal the source of the security breaches and achieve timely isolation before the whole process becomes uncontrollable.

3) DATA-DRIVEN AND KNOWLEDGE-BASED ADAPTIVE DIAGNOSIS

In the condition of highly dynamic topology changes due to the flexible connectivity and the openness of the system, the plant-wide system has an evolving characteristic. Reconfiguration and maintenance of the monitoring system itself will become overloaded. To improve this, contextual data will be used to adapt to the variations in the system configuration and the external environment—the heterogeneous data can be under unified management, and further, used to synchronize the correspondences in the physical world and the virtual redundancy. This is one of the main targets of the DT technique. Compared with the traditional model-based adaptive compensation approaches, data-driven techniques facilitate the adaptiveness in large-scale complex systems by constructing unified information containers.

To transform new expert knowledge into executable instructions/commands at the online stage is another favorable capability. As aforementioned, safety issues have become deeply intertwined with cyber-security issues. When a new security breach is identified, knowledge-based preventive monitoring will be activated.

4) RESILIENT CONTROL AND FULL LIFE-CYCLE MANAGEMENT

Performance supervised plant-wide process monitoring can provide valuable information for the closed-loop control and decision-making tasks. Resilient control refers to the control strategy that aims to minimize the multi-dimensional performance loss in case of unexpected events. It is straightforward that the monitored indices from the E&A network can provide comprehensive supports for the formulation of multi-objective optimization problems. The high-level decision-makers will have quantized information about the macroscopic control performance and will get to know precisely the impact of the unexpected events in advance.

From the perspective of life cycle management, the plant-wide monitoring system acts as a basis to trigger major strategic decisions and the switching of the control strategies, such as to achieve an optimal trade-off between the safety margin and the overall performance. Beyond monitoring the operating processes, it will be generalized to cover the full life cycle of "design–manufacturing–assembly–commissioning–operating–maintenance–decommissioning," and even linked with the procurement and the marketing processes at the business-end.

5) GROUND-UP COMPATIBILITY WITH THE SECURITY DESIGN

From the algorithmic perspective, the plant-wide monitoring system will be equipped with the capabilities of online attack modeling, threat assessment, as well as defense mechanism analysis (prognosis) [99]. From the implementation perspective, some compatible standards proposed in the Industry 4.0 pyramid can be adopted. For instance, OPC UA is an open standard that specifies information exchange for industrial communication needs [101]. OPC UA covers all the layers from the bottom component level to the top plant-wide decision level, including those in Fig. 3. It can be used across platforms and applies to Internet/Ethernet-based CPSs. Furthermore, the most attractive feature lies in its ground-up security design that considers both the data trustworthiness (in terms of confidentiality, integrity, and availability) and access control (in terms of authentication, authorization, and auditability) [102], [103]. This provides an intrinsic capability to defend the external cyber-physical attacks such as the DoS attack, replay attack, and false data injection attack.

6) AUXILIARY KEY TECHNOLOGIES

Apart from the aforementioned visions and directions that are directly related to the monitoring tasks, which are the main domain of study for the system and control experts, there are also several key open questions in other disciplines (e.g., computer science and technology).

First, efforts are required to manage the real-time process data and different types of internal and external information. For this purpose, the implementation of the physical containers in a unified framework is an important foundation. The potential containers include the cloud servers, the fog computing nodes, and the dedicated databases for knowledge graph [97], [104]. Authors in [105] highlighted the challenges related to operational-log analysis. In terms of computing power, authors in [106] discussed the new computing paradigm how the interconnection between the cloud, fog, and edge computing is expected, as well as some open questions in the communication layer.

Second, to better acquire real-time operation status, the sensing and cognition abilities of the system are to be improved with the machine vision techniques. Image or video-based soft sensing has demonstrated great potentials to deal with harsh working conditions beyond the applicable limit of the traditional sensors [107]. These research will facilitate the transformation from image to knowledge, and from knowledge to executable adjustment of the monitoring units. Accompanied by this, intensive examination of the data sources is required, especially for PnP devices such as webcams. Before granting full access, the access point and the related subsystems should run in the "sandbox mode". The trustworthiness of the PnP device and the data integrity must be inspected to ensure reliability regarding the interpretation of the perception results.

Third, digital twin technology is essential as a multifaceted replica that bridges the physical entities and the virtual space. In terms of individual devices, by taking advantage of the property of full life-cycle modeling, it is expected to achieve an elevation in the prognosis performance in a multi-time-scale manner [108]. Performance supervised monitoring is optimized by integrating the (short-term) monitoring of system dynamics and the (long-term) prediction of performance degradation. In terms of plant-wide systems, simulation-based deduction is a useful application based on the digital twin [61]. It is still an open question on how to fuse expert knowledge in the decision-making process to determine the degree of emergency and the required maintenance level. To approach this, semantic recognition, construction of the knowledge graph, and multi-threaded reasoning along the E&A network are needed.

VII. CONCLUSION

This paper rethinks the technical route of performance supervised plant-wide process monitoring. With more practical issues in large-scale industries taken into consideration, especially to deal with the challenges introduced by the autonomous units and the participation of humans, it is proposed to develop new schemes in the CPSS design framework. For this purpose, an alternative research route is proposed where the construction of performance evaluation systems and the development of performance-oriented fault diagnosis approaches play the central role. The roles of the performance evaluation indices and the existing approaches to calculate them are investigated in detail. On this basis, the existing performance-oriented and plant-wide monitoring approaches are reviewed, and the current practice to deal with the distributed implementation problem is summarized. Furthermore, the future research directions and an outlook about the future prospect are presented.

ACKNOWLEDGMENT

The authors would like to thank the EiC, the AE, and the anonymous reviewers who provided constructive suggestions and helped to elevate the quality of this work.

REFERENCES

[1] A. W. Colombo, S. Karnouskos, O. Kaynak, Y. Shi, and S. Yin, "Industrial cyberphysical systems: A. backbone of the fourth industrial revolution," *IEEE Ind. Electron. Mag.*, vol. 11, no. 1, pp. 6–16, Mar. 2017.

[2] J. Ding, H. Modares, T. Chai, and F. L. Lewis, "Data-based multi-objective plant-wide performance optimization of industrial processes under dynamic environments," *IEEE Trans. Ind. Informat.*, vol. 12, no. 2, pp. 454–465, Apr. 2016.

[3] Z. Gao, "Fault estimation and fault-tolerant control for discrete-time dynamic systems," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3874–3884, Jun. 2015.

[4] S. Xie, Y. Xie, H. Ying, Z. Jiang, and W. Gui, "Neuro-fuzzy-based plant-wide hierarchical coordinating optimization and control: An application to zinc hydrometallurgy plant," *IEEE Trans. Ind. Electron.*, vol. 67, no. 3, pp. 2207–2219, Mar. 2020, doi: 10.1109/TIE.2019.2902790.

[5] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques-part i: Fault diagnosis with model-based and signal-based approaches," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3757–3767, Jun. 2015.

[6] K. Paridari *et al.*, "A framework for attack-resilient industrial control systems: Attack detection and controller reconfiguration," *Proc. IEEE*, vol. 106, no. 1, pp. 113–128, 2018.

[7] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part II: Fault diagnosis with knowledge-based and hybrid/active approaches," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3768–3774, Jun. 2015.

[8] Y. Jiang, S. Yin, and O. Kaynak, "Data-driven monitoring and safety control of industrial cyber-physical systems: Basics and beyond," *IEEE Access*, vol. 6, pp. 47 3 47–47 384, 2018.

[9] X. Dai and Z. Gao, "From model, signal to knowledge: A. data-driven perspective of fault detection and diagnosis," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2226–2238, Nov. 2013.

[10] C. J. Parris, "Minds Machines: Meet a Digital Twin," 2016. [Online]. Available: https://www.youtube.com/watch?v=2dCz3oL2rTw

[11] Z. Ge and J. Chen, "Plant-wide industrial process monitoring: A. distributed modeling framework," *IEEE Trans. Ind. Informat.*, vol. 12, no. 1, pp. 310–321, Feb. 2016.

[12] Q. Jiang, X. Yan, and B. Huang, "Review and perspectives of data-driven distributed monitoring for industrial plant-wide processes," *Ind. Eng. Chem. Res.*, doi: 10.1021/acs.iecr.9b02391.

[13] R. S. Smith, "Covert misappropriation of networked control systems," *IEEE Control Syst. Mag.*, vol. 35, no. 1, pp. 82–92, Feb. 2015.

[14] S. Karadayi-Usta, "An interpretive structural analysis for industry 4.0 adoption challenges," *IEEE Trans. Eng. Manag.*, vol. 67, no. 3, pp. 973–978, Aug. 2020.

[15] Y. Jiang, K. Li, and S. Yin, "Cyber-physical system based factory monitoring and fault diagnosis with plant-wide performance optimization," *IEEE Int. Conf. Ind. Cyber-Phys. Syst*, pp. 240–245, 2018.

[16] Z. Chen *et al.*, "A distributed canonical correlation analysis-based fault detection method for plant-wide process monitoring," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp 2710–2720, May 2019.

[17] J. Zhu, Z. Ge, and Z. Song, "Distributed parallel PCA for modeling and monitoring of large-scale plant-wide processes with big data," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 1877–1885, Aug. 2017.

[18] D. Zumoffen, L. Braccia, and P. Luppi, "Data-driven plant-wide control performance monitoring," *Ind. Eng. Chem. Res.*, vol. 58, pp. 6576–6591, 2019.

[19] J. Hemilä and J. Jansson, "Business view on the development of industrial plant-wide optimization tool," in *Proc. Int. Conf. Prod. Operations Manage. Soc.*, 2018, doi: 10.1109/POMS.2018.8629458.

[20] T. Bi, J. Guo, K. Xu, L. Zhang, and Q. Yang, "The impact of time synchronization deviation on the performance of synchrophasor measurements and wide area damping control," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1545–1552, Jul. 2017.

[21] S. Yin, S. X. Ding, A. Haghani, H. Hao, and P. Zhang, "A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process," *J. Process Control*, vol. 22, no. 9, pp. 1567–1581, 2012.

[22] S. Ding, *Data-Driven Design of Fault Diagnosis and Fault-Tolerant Control Systems*, London, U.K.: Springer-Verlag, 2013.

[23] L. Ma, J. Dong, K. Peng, and C. Zhang, "Hierarchical monitoring and root-cause diagnosis framework for key performance indicator-related multiple faults in process industries," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2091–2100, Apr. 2019.

[24] S. Yin, J. Rodriguez, and Y. Jiang, "Real-time monitoring and control of industrial cyber- physical systems," *IEEE Ind. Electron. Mag.*, vol. 13, no. 4, pp. 38–47, Dec. 2019.

[25] Y. Jiang and S. Yin, "Recent advances in key-performance-indicator oriented prognosis and diagnosis with a MATLAB toolbox: DB-KIT," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 2849–2858, May 2019, doi: 10.1109/TII.2018.2875067.

[26] Z. Ge and Z. Song, "Distributed PCA model for plant-wide process monitoring," *Ind. Eng. Chem. Res.*, vol. 52, pp. 1947–1957, 2013.

[27] D. A. Bishop, "Key performance indicators: Ideation to creation," *IEEE Eng. Manag. Rev.*, vol. 46, no. 1, pp. 13–15, 2018.

[28] Z. Cao, X. Liu, J. Hao, and M. Liu, "Simultaneous prediction for multiple key performance indicators in semiconductor wafer fabrication," *Chin. J. Electron.*, vol. 25, no. 6, pp. 1159–1165, 2016.

[29] K. Zhang, H. Hao, and Z. Chen, "A comparison and evaluation of key performance indicator-based multivariate statistics process monitoring," *J. Process Control*, vol. 33, pp. 112–126, 2015.

[30] J. Chen, H. Jing, Y. Chang, and Q. Liu, "Gated recurrent unit based recurrent neural network for remaining useful life prediction of nonlinear deterioration process," *Rel. Eng. System Saf.*, vol. 185, pp. 372–382, 2019.

[31] F. Yang, M. Habibullah, T. Zhang, Z. Xu, P. Lim, and S. Nadarajan, "Health index-based prognostics for remaining useful life predictions in electrical machines," *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2633–2644, Apr. 2016.

[32] M. Jelali, *Control Performance Management in Industrial Automation: Assessment, Diagnosis and Improvement of Control Loop Performance*, London, U.K.: Springer-Verlag, 2013.

[33] B. Huang and S. L. Shah, *Performance Assessment of Control Loops: Theory and Applications*. Berlin, Germany: Springer, 1999.

[34] Q. Lu *et al.*, "Performance assessment of cross-directional control for paper machines," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 1, pp. 208–221, Jan. 2017.

[35] L. Das, B. Srinivasan, and R. Rengaswamy, "Multivariate control loop performance assessment with hurst exponent and mahalanobis distance," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 3, pp. 1067–1074, May 2016.

[36] O. Namaki-Shoushtari and B. Huang, "Bayesian control loop diagnosis by combining historical data and process knowledge of fault signatures," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3696–3704, Jun. 2015.

[37] J.-M. Cano-Izquierdo, J. Ibarrola, and M. A. Kroeger, "Control loop performance assessment with a dynamic neuro-fuzzy model (dFasArt)," *IEEE Trans. Automat. Sci. Eng.*, vol. 9, no. 2, pp. 377–389, Apr. 2012.

[38] T. Koenings, M. Krueger, H. Luo, and S. X. Ding, "A data-driven computation method for the gap metric and the optimal stability margin," *IEEE Trans. Autom. Control*, vol. 63, no. 3, pp. 805–810, Mar. 2018.

[39] C. Liu, B. Huang, and Q. Wang, "Control performance assessment subject to multi-objective user-specified performance characteristics," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 682–691, May 2011.

[40] F. Lewis, D. Vrabie, and V. Syrmos, *Optimal Control*. Hoboken, NJ, USA: Wiley, 2012.

[41] P. E. Aqueveque, E. P. Wiechmann, J. Herrera, and E. J. Pino, "Measurable variables in copper electrowinning and their relevance to predicting process performance," *IEEE Trans. Ind. Appl.*, vol. 51, no. 3, pp. 2607–2614, May-Jun. 2015.

[42] S. X. Ding, S. Yin, K. Peng, H. Hao, and B. Shen, "A novel scheme for key performance indicator prediction and diagnosis with application to an industrial hot strip mill," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2239–2247, Nov. 2013.

[43] Y. Duan, M. Liu, and M. Dong, "A metric learning based nonlinear modeling algorithm and its application in key-performance-indicator prediction," *IEEE Trans. Ind. Electron.*, vol. 67, no. 8, pp. 7073–7082, Aug. 2020, doi: 10.1109/TIE.2019.2935979.

[44] Y. Meidan, B. Lerner, G. Rabinowitz, and M. Hassoun, "Cycle-time key factor identification and prediction in semiconductor manufacturing using machine learning and data mining," *IEEE Trans. Semicond. Manuf.*, vol. 24, no. 2, pp. 237–248, May 2011.

[45] S. Yin and G. Wang, "Robust PLS approach for KPI related prediction and diagnosis against outliers and missing data," *Int. J. Syst. Sci.*, vol. 45, no. 7, pp. 1375–1382, 2014.

[46] S. Deb, N. Ray Choudhury, R. Ghosh, B. Chatterjee, and S. Dalai, "Short time modified hilbert transform-aided sparse representation for sensing of overhead line insulator contamination," *IEEE Sensor J.*, vol. 18, no. 19, pp. 8125–8132, Oct. 2018.

[47] T. P. Lambrou, C. C. Anastasiou, C. G. Panayiotou, and M. M. Polycarpou, "A low-cost sensor network for real-time monitoring and contamination detection in drinking water distribution systems," *IEEE Sensor J.*, vol. 14, no. 8, pp. 2765–2772, Aug. 2014.

[48] M. Y. Smirnov and G. D. Egbert, "Robust principal component analysis of electromagnetic arrays with missing data," *Geophysical J. Int.*, vol. 190, no. 3, pp. 1423–1438, 2012.

[49] K. Paridari *et al.*, "A framework for attack- resilient industrial control systems: Attack detection and controller reconfiguration," *Proc. IEEE*, vol. 106, no. 1, pp. 113–128, 2018.

[50] Y. Zhai, Y.-S. Ong, and I. W. Tsang, "The emerging "big dimensionality," *IEEE Comput. Intell. Mag.*, vol. 9, no. 3, pp. 14–26, Aug. 2014.

[51] D. Palacios and R. Barco, "Unsupervised technique for automatic selection of performance indicators in self-organizing networks," *IEEE Commun. Lett.*, vol. 21, no. 10, pp. 2198–2201, Oct. 2017.

[52] D. Zumoffen and E. Musulin, "Selection of controlled variables: A. novel perspective based on the singular energy of weighted graphs," *Comput. Chem. Eng.*, vol. 56, pp. 80–88, 2013.

[53] B. Krishnapuram, A. J. Hartemink, L. Carin, and M. A. Figueiredo, "A bayesian approach to joint feature selection and classifier design," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 9, pp. 1105–1111, Sep. 2004.

[54] M. Kang, M. Islam, J. Kim, and M. Pecht, "A hybrid feature selection scheme for reducing diagnostic performance deterioration caused by outliers in data-driven diagnostics," *IEEE Trans. Ind. Electron.*, vol. 63, no. 5, pp. 3299–3310, May 2016.

[55] R. Zhang, F. Nie, Y. Wang, and X. Li, "Unsupervised feature selection via adaptive multimeasure fusion," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 9, pp. 2886–2892, Sep. 2019.

[56] G. Ditzler *et al.*, "Extensions to online feature selection using bagging and boosting," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 9, pp. 4505–4509, Sep. 2018.

[57] Y.-R. Yeh, T.-C. Lin, Y.-Y. Chung, and Y.-C. F. Wang, "A novel multiple kernel learning framework for heterogeneous feature fusion and variable selection," *IEEE Trans. Multimedia*, vol. 14, no. 3, Jun. 2012.

[58] S. Munoz-Romero, V. Gomez-Verdejo, and J. Arenas-Garcia, "Regularized multivariate analysis framework for interpretable high-dimensional variable selection," *IEEE Comput. Intell. Mag.*, vol. 11, no. 4, pp. 24–35, Nov. 2016.

[59] J. Son, Y. Zhang, C. Sankavaram, and S. Zhou, "RUL prediction for individual units based on condition monitoring signals with a change point," *IEEE Trans. Rel.*, vol. 64, no. 1, pp. 182–196, 2015.

[60] T. Sutharssan *et al.*, "Prognostic and health management for engineering systems: A. review of the data-driven approach and algorithms," *J. Eng.*, vol. 2015, no. 7, pp. 215–222, Mar. 2015.

[61] M. Schluse, M. Priggemeyer, L. Atorf, and J. Rossmann, "Experimentable digital twins-streamlining simulation-based systems engineering for industry 4.0," *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1722–1731, Apr. 2018.

[62] S. Dusmez, H. Duran, and B. Akin, "Remaining useful lifetime estimation for thermally stressed power mosfets based on on-state resistance variation," *IEEE Trans. Ind Appl.*, vol. 52, no. 3, pp. 2554–2563, May-Jun. 2016.

[63] H. Miao, B. Li, C. Sun, and J. Liu, "Joint learning of degradation assessment and RUL prediction for aero-engines via dual-task deep LSTM networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 9, pp. 5023–5032, Sep. 2019, doi: 10.1109/TII.2019.2900295.

[64] C. Sun *et al.*, "Deep transfer learning based on sparse autoencoder for remaining useful life prediction of tool in manufacturing," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2416–2425, Apr. 2019.

[65] K. Javed, R. Gouriveau, and N. Zerhouni, "A new multivariate approach for prognostics based on extreme learning machine and fuzzy clustering," *IEEE Trans. Cybern.*, vol. 45, no. 12, pp. 2626–2639, 2015.

[66] W. Ahmad, S. A. Khan, and J.-M. Kim, "A hybrid prognostics technique for rolling element bearings using adaptive predictive models," *IEEE Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1577–1584, Feb. 2018.

[67] Y. Wang, Y. Peng, Y. Zi, X. Jin, and K.-L. Tsui, "A two-stage data-driven-based prognostic approach for bearing degradation problem," *IEEE Trans. Ind. Informat.*, vol. 12, no. 3, pp. 924–932, Jun. 2016.

[68] L. Liu, Q. Guo, D. Liu, and Y. Peng, "Data-driven remaining useful life prediction considering sensor anomaly detection and data recovery," *IEEE Access*, vol. 7, pp. 53 836–58 345, 2019.

[69] N. Li, Y. Lei, T. Yan, N. Li, and T. Han, "A wiener-process-model-based method for remaining useful life prediction considering unit-to-unit variability," *IEEE Trans. Ind. Electron.*, vol. 66, no. 3, pp. 2092–2101, Mar. 2019.

[70] M. S. Haque, S. Choi, and J. Baek, "Auxiliary particle filtering-based estimation of remaining useful life of IGBT," *IEEE Trans. Ind. Electron.*, vol. 65, no. 3, pp. 2693–2703, Mar. 2018.

[71] J. K. Kimotho, T. Hemsel, and W. Sextro, "Estimation of remaining useful lifetime of piezoelectric transducers based on self-sensing," *IEEE Trans. Rel.*, vol. 66, no. 3, pp. 914–923, Sep. 2017.

[72] F. Yang *et al.*, "Health index-based prognostics for remaining useful life predictions in electrical machines," *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2633–2644, Apr. 2016.

[73] Y. Lei *et al.*, "Machinery health prognostics: A. systematic review from data acquisistion to rul prediction," *Mech. Syst. Signal Process.*, vol. 104, pp. 799–834, 2018.

[74] W. Peng, Z.-S. Ye, and N. Chen, "Joint online RUL prediction for multivariate deteriorating systems," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 2870–2878, May 2019.

[75] J. I. Aizpurua, S. D. J. McArthur, B. G. Stewart, B. Lambert, J. G. Cross, and V. M. Catterson, "Adaptive power transformer lifetime predictions through machine learning and uncertainty modeling in nuclear power plants," *IEEE Trans. Ind. Electron.*, vol. 66, no. 6, pp. 4726–4737, Jun. 2019.

[76] V. Madonna, P. Giangrande, L. Lusuardi, A. Cavallini, C. Gerada, and M. Galea, "Thermal overload and insulation aging of short duty cycle, aerospace motors," *IEEE Trans. Ind. Electron.*, vol. 67, no. 4, pp. 2618–2629, Apr. 2020, doi: 10.1109/TIE.2019.2914630.

[77] A. Chehade and Z. Shi, "Sensor fusion via statistical hypothesis testing for prognosis and degradation analysis," *IEEE Trans. Automat. Sci. Eng.*, vol. 16, no. 4, pp. 1774–1787, Oct. 2019.

[78] A. E. Mejdoubi, H. Chaoui, J. Sabor, and H. Gualous, "Remaining useful life prognosis of supercapacitors under temperature and voltage aging conditions," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4357–4367, May 2018.

[79] P. Wouters, A. van Schijndel, and J. M. Wetzer, "Remaining lifetime modeling of power transformers: Individual assets and fleets," *IEEE Elect. Insul. Mag.*, vol. 27, no. 3, pp. 45–51, May-Jun. 2011.

[80] B. Radej and G. Beges, "An enhanced model for reliability prediction of a supercapacitor's lifetime," *IEEE Ind. Electron. Mag.*, vol. 13, no. 3, pp. 26–34, 2019.

[81] M. S. Ibrahim *et al.*, "Lumen degradation lifetime prediction for high power white LEDs based on the gamma process model," *IEEE Photon. J.*, vol. 11, no. 6, pp. 1–16, Dec. 2019, Art. no. 8201316, doi: 10.1109/JPHOT.2019.2950472.

[82] X. Fang, S. Lin, X. Huang, F. Lin, Z. Yang, and S. Igarashi, "A review of data-driven prognostic for IGBT remaining useful life," *Chin. J. Elect. Eng.*, vol. 4, no. 3, pp. 73–79, Sep. 2018.

[83] B. Sun *et al.*, "A review of prognostic techniques for high-power white LEDs," *IEEE Trans. Power Electron.*, vol. 32, no. 8, pp. 6338–6362, Aug. 2017.

[84] L. Liao and F. Kottig, "Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction," *IEEE Trans. Rel.*, vol. 63, no. 1, pp. 191–207, Mar. 2014.

[85] IEEE Reliability Society, IEEE standard framework for prognostics and health management of electronic systems (IEEE Std 1856-2017). *IEEE, 3 Park Avenue*, New York, NY 10016–5997 USA, 2017.

[86] N. Nise, *Control Systems Engineering*, 7th Ed., Hoboken, NJ, USA: Wiley, 2015.

[87] Q. C. Jiang, X. F. Yan, and B. Huang, "Performance-driven distributed PCA process monitoring based on fault-relevant variable selection and bayesian inference," *IEEE Trans. Ind. Electron.*, vol. 63, no. 1, pp. 377–386, Jan. 2016.

[88] Z. Chen, C. Yang, T. Peng, H. Dan, C. Li, and W. Gui, "A cumulative canonical correlation analysis-based sensor precision degradation detection method," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6321–6330, Aug. 2019.

[89] C. Alcala and S. Qin, "Reconstruction-based contribution for process monitoring," *Automatica*, vol. 45, no. 7, pp. 1593–1600, 2009.

[90] D. Hästbacka, P. Kannisto, and M. Vilkko, "Data-driven and event-driven integration architecture for plant-wide industrial process monitoring and control," in *Proc. 44th Annu. Conf. IEEE Ind. Electron. Soc.*, pp. 2979–2985, 2018.

[91] F. Boem, R. Carli, M. Farina, G. Ferrari-Trecate, and T. Parisini, "Distributed fault detection for interconnected large-scale systems: A scalable plug & play approach," *IEEE Trans. Control Networked Syst.*, vol. 6, no. 2, pp. 800–811, Jun. 2019.

[92] C. Zhao and H. Sun, "Dynamic distributed monitoring strategy for large-scale nonstationary processes subject to frequently varying conditions under closed-loop control," *IEEE Trans. Ind. Electron.*, vol. 66, no. 6, pp. 4749–4758, Jun. 2019.

[93] H. Luo, H. Zhao, and S. Yin, "Data-driven design of fog computing aided process monitoring system for large-scale industrial processes," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4631–4641, Oct. 2018.
[94] S. Vijaykumar, A. Dsouza, and S. Schaal, "Incremental online learning in high dimensions," *Neural Comput.*, vol. 17, no. 12, pp. 2602–2634, 2005.
[95] G. Wang, S. Yin, and O. Kaynak, "A LWPR based data-driven fault detection approach for nonlinear process monitoring," *IEEE Trans. Ind. Electron.*, vol. 10, no. 4, pp. 2016–2023, Nov. 2014.
[96] H. Chen, B. Jiang, and N. Lu, "An improved incipient fault detection method based on Kullback-Leibler divergence," *ISA Trans.*, 2018. [Online]. Available: https://doi.org/10.1016/j.isatra.2018.05.007
[97] D. Georgakopoulos, P. P. Jayaraman, M. Fazia, M. Villari, and R. Ranjan, "Internet of things and edge cloud computing roadmap for manufacturing," *IEEE Cloud Comput.*, vol. 3, no. 4, pp. 66–73, Jul./Aug. 2016.
[98] R. Saracco, Digital twins fueling the digital transformation, IEEE Future Directions Blogs, 2019. [Online]. Available: https://cmte.ieee.org/futuredirections/2019/03/12/digital-twins-fueling%-the-digital-transformation/
[99] S. M. Dibajia *et al.*, "A systems and control perspective of CPS security," *Annu. Rev. Control*, vol. 47, pp. 394–411, 2019.
[100] D. D'Elia, "The economics of cybersecurity: From the public good to the revenge of the industry," *First Workshop, Cyberics*, pp. 3–15, Vienna, Austria, Sep. 21-22, 2015.
[101] D. Bruckner *et al.*, "An introduction to OPC UA TSN for industrial communication systems," in *Proc. IEEE*, vol. 107, no. 6, pp. 1121–1131, 2019.
[102] S. Gruner, J. Pfrommer, and F. Palm, "RESTful industrial communication with OPC UA," *IEEE Trans. Ind. Informat.*, vol. 12, no. 5, Oct. 2016.
[103] P. Pop, M. L. Raagaard, M. Gutierrez, and W. Steiner, "Enabling fog computing for industrial automation through time-sensitive networking (TSN)," *IEEE Commun. Standards Mag.*, vol. 2, no. 2, pp. 55–61, Jun. 2018.
[104] G. Wang, M. Nixon, and M. Boudreaux, "Toward cloud-assisted industrial iot platform for large-scale continuous condition monitoring," in *Proc. IEEE*, vol. 107, no. 6, pp. 1193–1205, 2019.
[105] A. Miranskyy, A. Hamou-Lhadj, E. Cialini, and A. Larsson, "Operational-log analysis for big data systems: Challenges and solutions," *IEEE Softw.*, vol. 33, no. 2, pp. 52–59, Mar./Apr. 2016.
[106] J. Jasperneite, T. Sauter, and M. Wollschlaeger, "Why we need automation models: Handling complexity in industry 4.0 and the internet of things," *IEEE Ind. Electron. Mag.*, vol. 14, no. 1, pp. 29–40, Mar. 2020.
[107] Y. Xu, S. Ding, H. Luo, and S. Yin, "A real-time performance recovery framework for vision-based control systems," *IEEE Trans. Ind. Electron.*, vol. 68, no. 2, pp. 1571–1580, Feb. 2021, doi: 10.1109/TIE.2020.2967678.
[108] X. Si, Z. Ren, X. Hu, C. Hu, and Q. Shi, "A novel degradation modeling and prognostic framework for closed-loop systems with degrading actuator," *IEEE Trans. Ind. Electron.*, vol. 67, no. 11, pp. 9635–9647, Nov. 2020.

YUCHEN JIANG (Student Member, IEEE) received the B.E. degree (first-class Hons.) in automation in 2016 from the Harbin Institute of Technology, Harbin, China, where he is currently working toward the Ph.D. degree with the Department of Control Science and Engineering. During 2019 to 2020, he was a Visiting Student Researcher with Technische Universität München with Lehrstuhl für Steuerungs- und Regelungstechnik, Munich, Germany.

His research interests include data-driven process monitoring, fault diagnosis and prognosis, industrial cyber-physical systems, and artificial intelligence.

SHEN YIN (Senior Member, IEEE) received the M.Sc. and Ph.D. (Dr.-Ing.) degree from the University of Duisburg-Essen, Germany. He is currently DNV-GL Professor with the Department of Mechanical and Industrial Engineering, Norwegien University of Science and Technology.

His research interests include safety, reliability of complicated systems, system and control theory, data-driven and machine learning approaches, applications in large-scale systems and industrial cyber-physical systems.

OKYAY KAYNAK (Life Fellow, IEEE) received the B.Sc. (first-class Hons.) and the Ph.D. degrees in electronic and electrical engineering from the University of Birmingham, Birmingham, U.K., in 1969 and 1972, respectively.

From 1972 to 1979, he held various positions within the industry. In 1979, he joined the Department of Electrical and Electronics Engineering, Bogazici University, Istanbul, Turkey, where he is currently a Professor Emeritus, holding the UNESCO Chair on Mechatronics and also a "1000 Talents Program" Professor with the University of Science and Technology Beijing, China. He has held long-term (near to or more than a year) Visiting Professor/Scholar positions at various institutions in Japan, Germany, USA, Singapore and China. His current research interests include the fields of intelligent control and CPS. He has authored three books and edited five and authored or coauthored more than 400 papers that have appeared in various journals, books, and conference proceedings.

Dr. Kaynak has been on many committees of the IEEE and was the President of IEEE Industrial Electronics Society during 2002–2003. He has recently received the Chinese Government's Friendship Award and Humboldt Research Prize.