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# Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook

*Today's manufacturing systems are becoming increasingly complex, dynamic, and connected. The factory operations face challenges of highly nonlinear and stochastic activity due to the countless uncertainties and interdependencies that exist. Recent developments in artificial intelligence (AI), especially Machine Learning (ML) have shown great potential to transform the manufacturing domain through advanced analytics tools for processing the vast amounts of manufacturing data generated, known as Big Data. The focus of this paper is threefold: (1) review the state-of-the-art applications of AI to representative manufacturing problems, (2) provide a systematic view for analyzing data and process dependencies at multiple levels that AI must comprehend, and (3) identify challenges and opportunities to not only further leverage AI for manufacturing, but also influence the future development of AI to better meet the needs of manufacturing. To satisfy these objectives, the paper adopts the hierarchical organization widely practiced in manufacturing plants in examining the interdependencies from the overall system level to the more detailed granular level of incoming material process streams. In doing so, the paper considers a wide range of topics from throughput and quality, supervisory control in human–robotic collaboration, process monitoring, diagnosis, and prognosis, finally to advances in materials engineering to achieve desired material property in process modeling and control.*
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## 1 Introduction

Manufacturing is entering a period of substantial innovation and change driven by the increased integration of sensors and the Internet-of-things (IoT), increased data availability, and advances in robotics and automaton. This leads to pervasive digitalization of the factory and challenges manufacturing enterprises to reconsider, reexamine, and reevaluate their present operations and future strategic directions in the new era known as Smart Manufacturing and Industry 4.0 [1]. These innovations representing a future vision of manufacturing motivate the central theme of this paper, namely to examine how artificial intelligence (AI) can play a vital role in realizing these opportunities to advance the manufacturing industry in a profound new manner. To date, the implementation of AI in modern manufacturing has been built on the progressive development of a series of techniques over many decades, such as machine learning (ML) [2]. Recent advances in computational hardware as well as in sensing technology for the collection of critical process/machine data have made the application of these AI techniques feasible in a practical sense and led to a great interest in the capabilities and benefits that they offer. Further, a review of state-of-the-art AI applications helps to identify some unique manufacturing problems where AI techniques might provide solutions and thus significantly improve productivity, quality, flexibility, safety, and cost. Such knowledge and understanding are of great benefit to the practical implementation of AI in today's highly complex industrial environments that each has its own individual requirements and context.

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**1.1 Evolution of Artificial Intelligence.** AI can be defined as the "ability of computers to perform cognitive functions associated with human minds, such as perceiving, reasoning, learning, and problem solving" [3]. The term "AI" dates back to the 1950s with the invention in 1956 of the perceptron, a neural network (NN) structure designed to simulate a human neural system by utilizing a weighted sum of inputs [2,4]. Despite its roots in human learning mechanisms and widespread anticipation that human-like **cognitive** AI was well within reach, the development of perceptron was hampered by its inability to process even the simplest logic and intractable computational complexity [4]. This quickly led to reduced enthusiasm for supporting AI-related research and resulted in the beginning of the first AI winter. The recovery from the first AI winter was enabled by expert systems that correspondingly needed handcrafting by experts culminating in extensive series of "if-then" rules. This prevailing wisdom caused many to believe that expert knowledge was the best means to create AI. However, the era of knowledge-based AI turned out to be rather short-lived, as the expert systems became prohibitive in the design and maintenance of inherently complex logic, consequently leading to the second AI winter. ML contributed to the recovery of AI from the second winter, especially the invention of deep learning (DL), along with the advances in sensing and computational infrastructure that have allowed ML/DL models to be established [4,5]. These techniques are based upon generalization, meaning that they infer the general description of a class by observing the behavior of individuals in that class [4,5]. The expectation of AI has also been realigned to the more focused perspective of **enabling analytics**, whereby AI tools are a complement to the domain knowledge of human experts in the factory rather than their replacement [6–13].

**1.2 Opportunities for Artificial Intelligence in Manufacturing.** The main driving factors and requirements in most daily manufacturing operations across industries are those of meeting throughput, quality, and cost objectives while ensure a safe working environment for all. However, meeting these goals has become increasingly difficult with the multitude of demands stemming from growing product and process complexity, higher variability in customer demand and preferences, along with relentless competitive pressures from others in the marketplace to remain profitable. Seen from a positive perspective, this tough operating climate facing the majority of manufacturers provides an opportunity for the unique capabilities of AI over conventional tools and approaches. In particular, the commonplace activity of problem-solving which involves looking for root causes lends itself well to AI tools capable of identifying and classifying multivariate, nonlinear patterns in operational and performance data that are hidden to the plant engineer. Nowadays, huge amounts of continuously generated data are produced by machines, ambient sensors, controllers, and labor records, etc. The data could be categorized as follows: (1) environmental data collected from ambient sensors, e.g., room temperature and humidity, (2) process data collected from sensors on process machines or stations, e.g., machining and grinding coolant temperatures, power, and heat treat temperature/energy, (3) production operation data recorded in controller systems, e.g., timestamps or elapsed time of each part in each operation station, machine downtime, starvation/blockage, idle time, and shift scheduling, (4) measurement or check data from product quality inspections, e.g., product diameter, form, and balance. Embedded in all this big data are unprecedented opportunities for pattern discovery that can contain important clues to solve tough problems while offering a complementary understanding of the physical meaning of parameters to other physical characteristics of a system or process. Coupled with the ability to comprehend high dimensional data, AI provides the ability to transform large amounts of complex manufacturing data, which has become commonplace in today's factory, into actionable and insightful information [9–13].

**1.3 Hierarchical Approach to Manufacturing Systems.** The topic of AI in manufacturing has attracted much attention in the scientific community with the number of publications steadily growing over the past 40 years, as shown in Fig. 1. Recently, several review publications have also been published on this topic. In Refs. [7,8], a high-level, general framework and key elements in smart manufacturing systems and governmental initiatives around the globe are presented. The constituent technologies such as IoT, cyber-physical systems (CPS), cloud computing, big data analytics, and information and communications technology (ICT) and their interrelationships are discussed. A review of the ML and DL techniques and their applications in manufacturing is found in Refs. [9,10], respectively. In these publications, the focus was on the survey of the techniques themselves instead of the requirements derived from the manufacturing system. Several other review papers have focused on specific aspects in manufacturing, providing analysis at a more granular level with support from more detailed examples. For example, Refs. [11,12] discussed AI for machine condition monitoring and fault diagnosis, while Ref. [13] provides a comprehensive review of AI in the emerging field of human–robot collaboration (HRC).

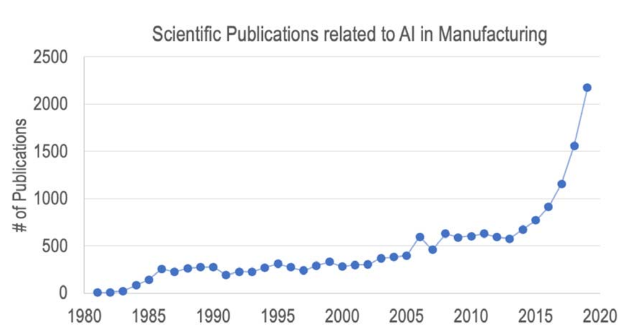


**Fig. 1 Growing scientific publications for AI in manufacturing**

Furthermore, since the topic of AI in manufacturing has witnessed this rapid growth in the amount of published research, to write a review paper such as this requires an organizing construct as a framework to help assess, review, and synthesize the vast literature in this field of ongoing research, development, and industrial implementation. Therefore, the review presented herein aims to strike a balance between a high-level overview of the advanced manufacturing systems and the specific AI techniques as representative examples. The uniqueness of this paper is that it follows a hierarchical view to classifying plant systems and processes since this is how plants are commonly organized, both physically and functionally, as illustrated in Fig. 2. This hierarchical view as an organizational construct is thus a valuable concept from the perspective of system requirements when reviewing the suitability of any AI technology to ensure global goals are met and sub-optimization is avoided. The hierarchical, three-level decomposition of the manufacturing system (system-process-material) also draws parallels from the ISA-95 framework that defines from the low-level physical processes (for which modeling of the material property plays an important role), to the mid-level sensing/monitoring of the processes (the foundation of maintenance and prognostics and health management, or PHM) and finally, the top-level managing manufacturing operation (the system-level modeling and performance analysis).[1]

Given that the field of AI as described above is very broad with a long history and theoretical underpinnings in statistics, optimization, and computer science, there is an overwhelming amount of literature to survey, and therefore, this paper has been scoped with three major objectives: (1) review the state-of-the-art applications of AI to important manufacturing problems, (2) provide and use a system-level view with which to understand data and process dependencies at the multiple levels that AI must comprehend, and (3) identify challenges and opportunities to not only further leverage AI, but to influence the future development of AI to better meet the needs of manufacturing.

With these goals in mind, this paper is organized following the hierarchical logic of Fig. 2. First, beginning from the overall system level, we examine AI in areas such as throughput and quality optimization in Sec. 2. Next, we look at a specific example of system control, namely that of human supervisory control in the context of HRC in Sec. 3. Following this, we proceed to the process level in Sec. 4, in which the analysis of signals from machines and processes provides new opportunities to advance the field of diagnosis and prognosis. Section 5 considers the opportunities provided by AI to improve material processing and characterization which are the fundamental building blocks for reducing the uncertainty of incoming material streams. Future challenges and opportunities are then summarized in Sec. 6, and overall conclusions are drawn at the end.

## 2 Artificial Intelligence for Manufacturing System Optimization

A manufacturing system can mean many things, depending on the viewpoint taken. In this paper, manufacturing systems comprise machines, robots, conveyors, and supporting activities such as maintenance and material handling arranged to produce the desired product, as shown in Fig. 3. Factory operations are highly nonlinear and stochastic due to countless uncertainties and interdependencies [14,15]. The performance (hence the global competitiveness) of such modern manufacturing systems is critically

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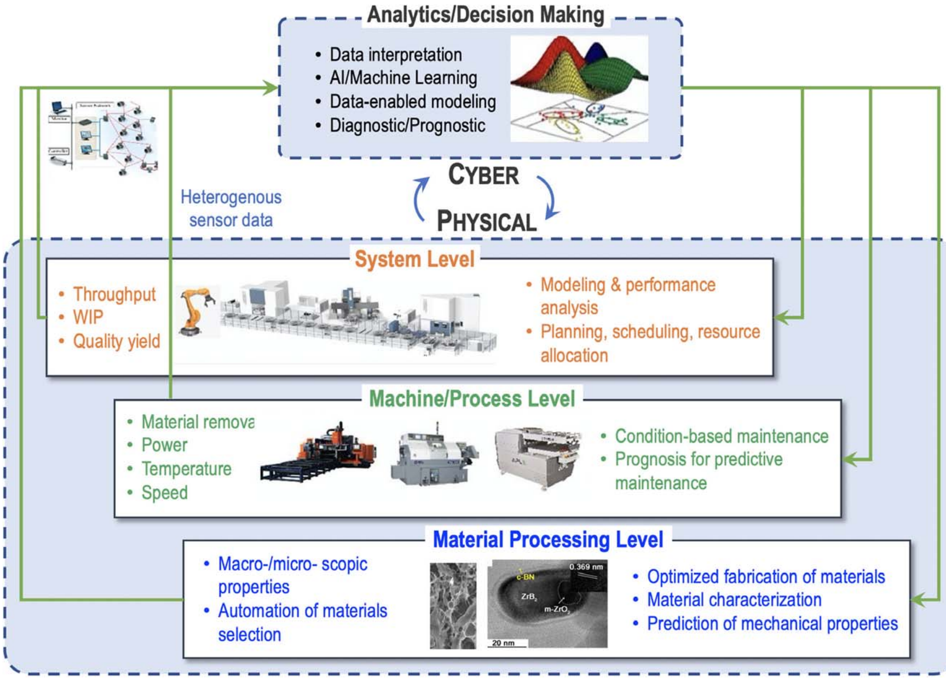


**Fig. 2 Hierarchical plant organization**

dependent on the "optimal control" of material flow through the work cells. This section aims to review the recent advancement in AI approaches as it applies to manufacturing systems including system modeling and performance analysis, and optimal system-level control and decision-making.

**2.1 Modeling and Performance Analysis.** Production system performance evaluation, diagnosis, and prognosis in terms of productivity, quality, and efficiency are of great importance. However, unreliable machines and finite buffers make the material flow in manufacturing systems difficult to model and analyze since the former makes it stochastic and the latter nonlinear.

*2.1.1 Throughput Evaluation.* Throughput analysis is aimed at evaluating long-term or short-term productivity of manufacturing systems, which could facilitate system design, performance improvement, and daily operation of production systems. Substantial amounts of research have been devoted to the analysis of manufacturing system dynamics and performance [15–19]. However, the traditional analytical modeling methods based on queuing theory and Markov Chains [17,18,20,21] suffer from two considerable disadvantages. The adoption of data analytics and ML techniques offer great potential to compensate for these shortcomings.

First, the analytical methods for estimating throughput, either exact or approximate, are limited to simple system structures under strict assumptions. For more complex systems, simulation turns out to be the only feasible approach to evaluate long-term system performance. ML methods can be applied to generalize the results from simulations, to avoid repetitive simulation runs when the production system parameters are changed. In Ref. [22], the gray model and neural network are combined to predict system throughput for a multi-product production line considering rework loops. In Ref. [23], a single hidden layer neural network is trained to predict makespan and throughput for multi-product manufacturing systems considering stochastic cycle times.

Second, conventional throughput improvement approaches focus mainly on long-term steady-state performance analysis, which are not applicable to real-time throughput prediction and production

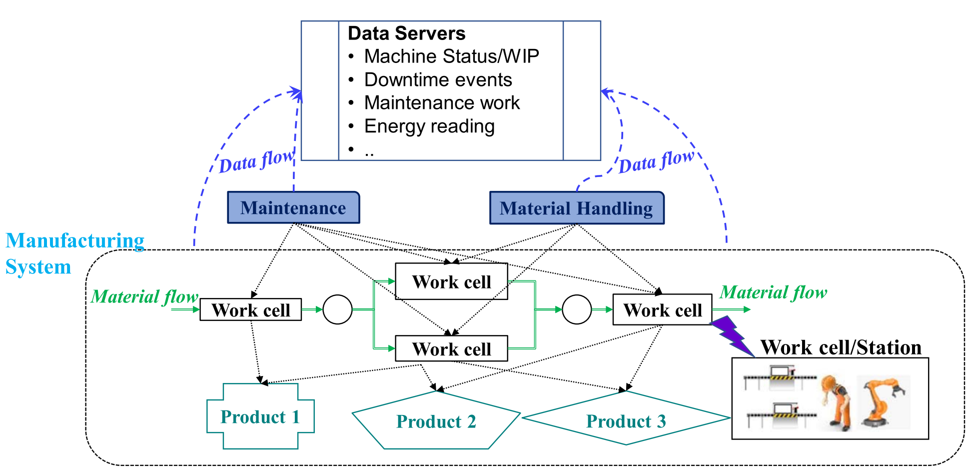


**Fig. 3 Schematic of a modern manufacturing system**

control. Further, they are unable to take full advantage of today's vastly superior sensor readings. Short-term system performance, inferred from buffer states and machine status, has proven to be useful in real-time control for complex production systems [24,25]. Improving production system throughput is an important task of production line management and control. In practice, it is often accomplished by identifying the bottleneck machine and improving its operation. Data-driven methods in identifying throughput bottlenecks have been extensively studied. Earlier works [15,18] develop an indirect index to identify production bottlenecks. In Ref. [26], an event-based method is discussed to evaluate permanent production loss in battery manufacturing. In Ref. [27], a data-driven model is developed using available sensor data, and a system diagnostic method is proposed to identify real-time production constraints and bottlenecks. In Ref. [28], a recency-weighted stochastic learning method is proposed to predict the system production losses of serial production lines in a small look-ahead window.

*2.1.2 Quality Analysis.* The complex interactions among different processes in multistage manufacturing systems have presented significant challenges for quality analysis in the system level. Classical statistics-based approaches, e.g., control charts and run charts, which mainly focus on process-level quality assurance, might not be applicable to system-level analysis, since the quality deviation in a particular stage is not only determined by that stage but also by upstream stages or sub-assemblies. Model-based methods for quality analysis, e.g., the stream-of-variation model [29], provide an analytical approach to examine quality issues through modeling the generation and propagation of quality variations. However, model-based methods often require substantial domain knowledge that is not always readily available. ML-based quality analysis is well suited to situations where there is limited if any, domain knowledge regarding the process physics and system dynamics. These analysis approaches have been found to achieve one or more of the following objectives by applying the AI/ML-based methods.

(1) *Early detection of quality defects*. For multistage manufacturing systems, undesirable quality deviations might propagate along stages and result in defects of final products. It is of great benefit to detect quality deviations in earlier stages, which would save production resources and reduce the overall cost by promptly reworking defective parts. Conventionally, statistical process control (SPC) is commonly used to monitor the quality of work-in-process parts by inspecting several important variables according to given specification ranges. Despite its widespread usage, SPC has its drawbacks in that, for example, the data are assumed to be unimodal, which is not always true. More importantly, SPC is dependent on clear, known relationships between inspected variables and final product quality. With the vast amounts of time-series data, some ML-based approaches [30–35] are proposed to effectively overcome some of the deficiencies in conventional process control methods. In Ref. [34], a case study is presented on the quality control of work-in-progress products in the powder metallurgy process based on autoencoders and recurrent neural networks (RNNs). In Ref. [35], a combination of cluster analysis and support vector machines (SVM) is introduced to achieve the goal of improved quality monitoring. Compared with quality prediction, the early detection of quality defects is more challenging since the latter needs to discover the relationship between incomplete observations up to specific stages and quality characteristics of the final product with time-series data.

(2) *Root cause diagnosis of quality issues.* In multistage manufacturing, one defective product might result from one or multiple imperfect quality stages. Identifying the root cause for quality issues is of great practical value in industries since corrective actions can be taken promptly to improve product quality. However, due to the fact that system-level quality diagnosis requires intensive expert knowledge, the applications of pure ML methods in this context are limited. Bayesian networks are one of the methods that can be used to conduct root cause diagnosis of quality issues as it is convenient to infer fault causes from observed quality deviations. In Ref. [36], a new method of Bayesian network construction is proposed, using a framework designed for root cause diagnosis in an automotive body assembly process. The proposed method can work with small data sets and medium-level noise in measurements. In Ref. [37], a distributed diagnostic framework based on a multi-agent Bayesian approach is proposed and implemented in a lab-based modular assembly system.

**2.2 Manufacturing System Decision-Making and Control.** Manufacturing system control is concerned with decision-making and controlling of the physical activities in a factory in order to improve productivity, quality, and overall efficiency. Algorithms at the system level are used to decide what and how much to produce, when production is to be finished, how and when to use the resources or make them available, when to release jobs and which jobs to release, job routing, and job/operation sequencing [38]. The approaches can be categorized into centralized or hierarchical control approaches and distributed multi-agent-based control approaches. Traditional centralized manufacturing control approaches and software packages are developed and adapted case by case and lack flexibility, expandability, agility, and reconfigurability [38]. On the other hand, multi-agent-based control approaches derived from distributed AI techniques provide several important benefits such as robustness, reconfigurability, and responsiveness [39].

Smart manufacturing seeks to increase factory productivity and the efficient utilization of resources in real-time [40]. To achieve these objectives, manufacturing systems need to transform large amounts of data into manufacturing knowledge and useful actions in order to become more responsive to market changes and random disruption events. It is crucial to consider adaptive planning, scheduling, and control for dynamic manufacturing environments as key research issues in smart manufacturing management.

*2.2.1 Job Dispatching and Scheduling.* In flexible manufacturing systems, the job dispatching problem arises when there are multiple product orders awaiting processing during the same time window. It is critical to determine which order should be prioritized and which machine should undertake the job. In this context, the job dispatching problem seeks to find the optimal job sequences and job routes considering various internal factors, e.g., machine capability and availability, and external factors, e.g., order due dates, such that one or more of the following minimizing objectives can be achieved: mean tardiness, mean stay time, and energy consumption. Over the past few decades, the job dispatching problem has been widely studied in the literature with many different reported approaches. Exact approaches, e.g., branch-and-bound (B&B) and integer programming, are feasible for small-scale job dispatching problems, while heuristic-based methods, e.g., simulated annealing and genetic algorithm, might deliver dispatching rules that lack adaptiveness to system dynamics [41]. To cope with the increasing complexity of manufacturing systems, ML-based methods, including both supervised learning and reinforcement learning (RL), have been extensively applied in this area.

Supervised learning involves learning from labeled examples provided by an expert with domain or application knowledge. Moreover, supervised ML is frequently used due to the data-rich but knowledge-sparse nature of problems in the manufacturing environment. Conventionally, simple heuristic dispatching rules are used in production scheduling, such as SPT (shortest process time), COVERT (cost over time), EDD (earliest due date), and FIFO (first in, first out) [42]. However, adhering to a single dispatching rule does not necessarily deliver better performance than dynamically switching dispatching rules according to system states. Inspired by observation, classification problems are formulated by taking the relevant system dynamic variables as inputs, and simple dispatching rules as outputs. Commonly used ML algorithms in this context include Decision Tree [43–45], Neural Network [46–48], SVM [41,49,50], and ensemble learning methods [41]. Despite the ML algorithms, the authenticity of training data is the prerequisite to reliable production scheduling. Although simulation (e.g., Refs. [41,46–49]) is a typical source for training data, it suffers from the disadvantage that data might be biased if the simulation is incapable of representing real operations. Therefore, researchers in Refs. [43,44,50] attempt to avoid such bias by aggregating multiple data sources, including simulation, historical data, and expert knowledge. In Ref. [45], a real-time, big data framework is established to collect, process, and store actual data from the shop floor upon which a real-time production scheduling and rescheduling method are implemented.

RL is suitable for a model-free problem with delayed consequences, in which the model dynamics are unknown and must be estimated through interactions of agents with the environment. The applications of RL methods in job dispatching problems are not new since job dispatching is a sequential decision-making problem in dynamic environments. Extensive RL-based research, including Refs. [51–54], has been reported for distinct applicable scenarios. In Ref. [51], by adopting the decentralized Markov decision process (DEC-MDP) framework, processing machines are modeled as distributed RL agents and a policy gradient algorithm is used to discover near-optimal dispatching rules. In Ref. [52], a relational RL approach is proposed to obtain policies for efficiently rescheduling production plans, which is able to handle abnormal and unplanned events such as inserting an arriving order. In Ref. [53], a scheduling method based on variable neighborhood search (VNS) is proposed to obtain job dispatching decisions considering random job arrivals and machine random failures, in which RL is used to obtain proper parameter for VNS at a rescheduling decision point. There are dozens of RL-based research approaches tackling the job dispatching problem where slightly over 80% of this work adopts the tabular Q-learning algorithm, a powerful, but hard to scale, off-policy RL algorithm. With the rapid advancement of RL in recent years, a great deal of novel algorithms have emerged, including the deep Q-network (DQN) [55], which is able to solve large-scale RL problems by integrating deep neural networks (DNN). In Ref. [54], the DQN is applied to solving a large-scale scheduling problem in a semiconductor manufacturing system. The novel RL algorithms like DQN, which have largely enhanced learning efficiency and scalability, are expected to help solve more sophisticated and practical production scheduling problems in the future.

Maintenance activities aim to keep machines in desirable reliability levels or to quickly recover them from random failures. As maintenance work orders can be modeled as a sequential decision-making problem given machine states and system states, RL has also been used in Refs. [56–60] to obtain near-optimal maintenance policies for manufacturing systems. Many studies [57,58,60] integrate multi-agent-based learning and control in their methods, helping dismantle complex structural and operational dependencies among components. Compared to traditional maintenance policies [61], e.g., periodic policy and age-dependent policy, the RL-based maintenance policies are more adaptive to the manufacturing system dynamics and therefore yield better system performance. The adaptiveness of the RL-based maintenance policies provides a great opportunity to build real-time maintenance decision-making systems by making full use of real-time data analytics on the plant floor. In Ref. [62], a conceptual framework for maintenance scheduling is proposed to schedule condition-based maintenance in smart manufacturing systems.

*2.2.2 Resource Allocation.* In a manufacturing system, resource allocation is the process of assigning manufacturing resources for specific time periods to the set of manufacturing processes, where resources include but are not limited to robots, human operators, and machines. Resource allocation is an optimization process whereby limited manufacturing resources are allocated over time among parallel and sequential activities in order to achieve a desirable system performance. Resource allocation problems may arise in both the design stage and daily operation. A typical resource allocation problem in the design stage is the buffer allocation problem [63], i.e., allocating buffer spaces to a production line given the total available spaces. In Ref. [64], a decision support system is proposed for buffer allocation, where a neural network is trained to quickly predict system throughput given system design parameters. The resource allocation problems in daily operations are further complicated by the highly uncertain and fast-evolving factory environments, compared with that in the design stage. In daily operations, resource allocation is often coupled with task assignments. RL has been widely applied to tackle problems in this area. In Ref. [65], an RL-based method is proposed for dispatching material handling dolly trains in a general assembly line, wherein the dolly train delivers materials to workstations and carries multiple types of parts at a time. In Ref. [66], a gantry assignment problem in production lines is also formulated as an RL problem and solved by the Q-learning algorithm. In both studies, random factors, such as machine failures in Ref. [66] and product queue lengths in Ref. [65], drive the transition of the system states, which are difficult to obtain the complete state transition models. RL fits such sequential decision-making problems well and can solve them in a model-free way with various algorithms. Nonetheless, RL problem formulation needs careful analysis and a thorough understanding of the system dynamics. In Ref. [67], a comprehensive simulation study is conducted on the same gantry assignment problem presented in Ref. [66] with a focus on comparing different reward settings, which demonstrates that the knowledge-guided reward setting outperformed all other four heuristic-based reward settings.

With the advancement of industrial IoT, AI and specifically ML will see increasing utilization penetrating the entire manufacturing system. ML algorithms potentially provide powerful tools to reduce cycle time and scrap, improve quality, and improve resource utilization in certain NP-hard manufacturing problems [68].

## 3 Artificial Intelligence for Manufacturing Applications of Human–Robot Collaboration

This section specifically examines the utilization of AI in the context of HRC. Consistent with this paper's use of a hierarchical framework to structure and organize the review of AI in manufacturing systems, the topic of HRC is one that uniquely straddles both the system and machine/process layers. HRC may be defined [13] as "a state in which a purposely designed robot system and an operator work on simultaneous tasks within a collaborative workspace, i.e., where the robot system and a human can perform tasks concurrently or even jointly." The impact of AI on HRC is particularly important to review given the continually increasing diversity and quantity of robotic applications in manufacturing. Traditionally, the objective of applying robotics in manufacturing has been to leverage the advantages robots have over humans such as repeatability, endurance, strength, ability to operate in hazardous environments, etc. Industry has long recognized that utilizing robots to perform these types of tasks frees human operators to more efficiently focus on their inherent natural advantages, namely, those related to cognition, adaptability, ambiguity, and flexibility. However, with the advent of increasingly more powerful and capable AI/ML tools, this relative balance of skills, functionality, and types of capabilities is continuously shifting and becoming less clear as the sophistication and computational power and application domain of these technologies increase.

Correspondingly, the body of work in HRC is a very broad set of industrial research areas that drives an equally diverse set of potentially applicable robot-related AI technologies. Reviewing such a resulting breadth and depth of literature is challenging without a roadmap that can offer guidance as to what has been developed, what is state of the art, and what important problem areas remain to be solved. While there can be no definitive or absolute categorization of such a vast field of work, as we have done for the overall paper, we also propose a framework adapted from human supervisory control theory and combine it with a classification scheme for describing the characteristics of HRC. In this manner, the resulting descriptive framework is used to cross-reference AI-based technologies with key aspects of HRC and therefore highlight foundational work and the problem domain for which AI/ML is either already being deployed, or in the future may be well suited to solving other more difficult problems.

**3.1 Overview of Human–Robot Collaboration.** Over the decades since robots were first introduced into industrial environments, manufacturers have sought to gain ever more efficiencies and capabilities from these significant capital investments. Simultaneously, the role of the human operators and the nature of the interaction with robots and robotic systems have evolved in conjunction with the increasing functionality and application space where they have been installed. However, with recent developments in many robot capabilities such as sensing, perception, control, teaching, and learning the very nature of the human–robot relationship is being examined with a focus toward attaining greater productivity, flexibility, and adaptability [69,70]. These benefits are driving manufacturing firms to move their human–robotic systems from one of coexistence toward collaboration.

However, despite the attraction of the potential benefits that HRC promises, there are still key technical challenges and requirements that need to be addressed and overcome before improvements in productivity can be realized. Chief among these are the industrial safety requirements that prohibit human operators and robots from sharing a common workspace, and as such is an ongoing area of research [71–73]. Other challenges concern how robots understand and interpret the uncertainty in the behavior, actions, and intentions of the human(s) that comprise an HRC system [74]. Nevertheless, advances are being made by some robot manufacturers to develop commercial robotic solutions that can begin to meet some of these challenges such as in industries having light-duty, low-powered, or low-payload applications. Though firms are developing innovative solutions to solve practical industrial problems, HRC still represents a large area of ongoing research before industry-wide adoption can occur. However, advances in AI technologies may enable and accelerate the development and implementation of HRC into the industry.

**3.2 Characterizing the Human–Robot Relationship.** When reviewing the literature, the type of AI techniques that have been developed and implemented for HRC depending on the specific details of the HRC manufacturing application such as the complexity and type of an assembly operation and on the nature of the human–robot relationship. The latter is particularly important as it governs how a manufacturing operation is executed jointly by the human and robot and warrants further examination. In this regard, four types of HRC have been defined [75] wherein the degree of collaboration is classified according to how closely humans and robots work together on a specific manufacturing operation comprised of processes and workpieces. These range from (i) complete independence of different processes and workpieces, (ii) synchronization of different processes with a common workpiece, (iii) simultaneous different processes and common workpiece, and (iv) simultaneous collaboration on common process and workpiece.

Further work [76] classifies various human–robot relationships from the perspective of sharing within five types of situations or scenarios, namely that of workspace, direct contact, work task, simultaneous process, and sequential process. These scenarios are then mapped to four different types of human–robot relationships: coexistence, interaction, cooperation, and collaboration. This tabular construct then permits a rich and comprehensive description of human–robot relationships that maybe used to describe particular human–robot operational environments.

**3.3 Human Supervisory Control at the Intersection of Human–Robot Collaboration.** Sheridan [77,78] defines a paradigm composed of human supervisory control functions wherein a human supervises a generalized machine whether it be an entire automation system, a robot, a computer, or any other physical device capable of receiving commands and carrying out actions correspondingly. The specific functions consist of planning, teaching, monitoring, intervening, and learning. However, in our paper, we augment these five functions with a sixth function, that of operating a system to explicitly call out task execution activities by both the human and robot in HRC systems. Though this section discusses a collaboration between a human and a robot, there is no loss in generality by considering the human as a supervisor in this collaborative setting since Sheridan's paradigm allows for varying degrees of supervision between humans and automation. Each of these six functions is potential area for the application of a wide variety of AI/ML tools since they are all fundamentally performed by a human supervisor. In this regard, Sheridan's classical paradigm of human supervisory control provides a suitable perspective through which to analyze human-collaborative robotic systems in manufacturing that seek to leverage recent advances in AI/ML. Given this well-established foundation, we reexamine the paradigm in light of today's advances in robotics to consider these six functions extended into the robotic domain as described in greater detail in Sec. 3.4.

**3.4 Integrated Perspective for Surveying Human–Robot Collaboration and Artificial Intelligence Manufacturing Literature.** Using the above foundation, we make use of Fig. 4 as an organizing framework to map AI/ML technologies to existing and potential industrial HRC applications and find common themes across problem types and corresponding AI/ML solutions.

*3.4.1 Plan.* Planning [77,78] comprises three elements and activities: system modeling, setting and meeting objectives, and formulating strategies. In an example of planning from an assembly application [79], Bayesian sequential decision-making is investigated to determine the optimal allocation of sensing modes between purely autonomous and manual states. A shared vision system is considered wherein a combination of observational modes exists ranging from solely human-based, mixed human–robot based, and solely robot based with the goal being to determine the optimal allocation decision among these three modes. In the development of "intelligent agents" [80], vision technology and planning activities are examined for how AI can integrate these two areas. Another facet of HRC planning [81], considers the assignment of roles and allocating tasks among the humans and robots in a collaborative system. Under the Sheridan supervisory control paradigm, it is given that the balance between roles and tasks is specified in the original system design. In Ref. [81], a framework is proposed for lab-based experiments of a human and robot collaborative system to assemble a basic household item of furniture that enables reasoning to make such types of decisions. This reasoning framework utilizes partially observable Markov decision processes (POMDP) capable of performing in uncertain environments thus providing the ability to plan adaptively. In other work [82], an "anticipatory control" method is developed to proactively plan robot actions based on anticipation of the human operator's intention during task performance. Here, the AI technique employed is that of an SVM to predict gaze patterns of the operator and in turn predict task intentions.

*3.4.2 Teach.* Secondly, teaching or training, involves communicating commands to a robot(s) execute specific actions. In an HRC assembly application [83], a machine learning framework is proposed to identify successful snap-fit assembly operations and

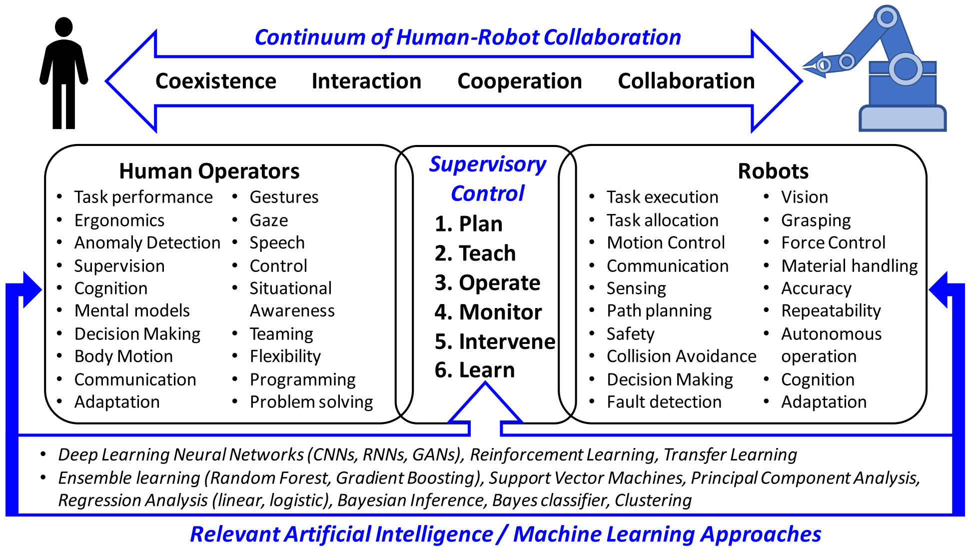


**Fig. 4 Illustrative sets of actions, functions, requirements, characteristics, and behaviors for human operators and robots which are candidates for application of AI/ML approaches**

transfer them from human to robotic operations. This framework utilizes force profile features to identify types of snap-fits based on data sets generated via HRC having high variability enabling machine learning, in this case, an SVM classifier was trained. This is an example of where HRC is used for training to develop autonomous robotic operations. In Ref. [84], a system based on natural language is proposed to improve the teaching and robot programming task. The system is built on a semantic network as the basis for a natural language processing system comprised of automatic speech recognition, visual simulation environment, and reasoning. Human voice commands are inputs to the reasoning system which also takes inputs from the natural language processor to search for a reasonable set of robotic actions. In this work, the semantic hierarchical network improves system robustness by preventing incorrect or irrelevant robotic tasks from occurring such as a robot picking up a worktable instead of a workpiece thus yielding faster object referencing.

*3.4.3 Operate.* Operation concerns the required active steps, processes, tasks that are completed independently, sequentially, or simultaneously by the human(s) and the robot(s) in HRC systems to achieve planned objectives. Depending on the type of application and system, these operational steps or processes may or may not be pre-planned which will accordingly drive the requirements of a given AI technique chosen to improve operational efficiencies. Moreover, the lack or inability to pre-plan HRC operations notwithstanding, an even greater challenge facing HRC is the inherent uncertainty and variability in human task performance times. Though it may be argued that such variability is the cost of flexibility provided by human operators, this characteristic of HRC nonetheless requires the development of approaches to ensure productivity is maintained. An online AI technique [85] developed for automatic and unsupervised clustering of basic HRC operational steps uses real-time force/torque data to address the challenge in human cycle time variability. The specific AI method developed and experimentally tested uses dynamically trained one-class support vector machines (OCSVMs) to discover states of manufacturing process steps. This type of online algorithm demonstrates the ability to realize real-time performance without the penalty of requiring labeled data from training phases.

*3.4.4 Monitor.* Next, monitoring requires the human operator or supervisor to continuously observe and evaluate the execution of the robots' actions and progress toward completion of all tasks and respond to any anomalous events that may arise during operation. Observing or monitoring includes analysis of the robot system data from many data sources and types while considering the overall system state as part of maintaining situational awareness. Considering robotic monitoring capabilities, the term "Internet of Robot Things" (IoRT) [86] describes intelligent devices that can monitor events, fuse sensor data from a variety of sources, use local and distributed intelligence to determine the best course of action. A system architecture that enables monitoring [87] can integrate observational factors such as work patterns during operation (discussed previously). RL is used in the estimation of factors such as human kinematics via a recursive least-square (RLS) algorithm. In a more comprehensive use of AI in monitoring [88], a deep learning-based multimodal fusion architecture is developed for the robust operation of an HRC manufacturing system. Three modes of communication between humans and robots are considered in this work: voice, hand motion, and body motion. These particular modalities for monitoring provide an intuitive approach for human supervisors or operators to interact with robots. Further, an architecture integrating these modes provides a more flexible alternative to the more prescriptive approaches of Refs. [81,89] and more closely represents the uncertain, stochastic nature of monitoring human performance interacting with robotic systems. Moreover, each of these individual modalities is addressed by a unique AI approach before multimodal fusion is carried out. Voice command recognition is formulated as a CNN, hand motions as an LSTM (RNN), and body motion makes use of MLP transfer learning.

*3.4.5 Intervene.* The fifth element of HRC relates to the intervention of operations and considers what alternative steps or corrective actions must be pursued if, in the course of monitoring, the human or robot observes the occurrence of a fault or anomaly. In human–robotic systems with limited interaction, a human supervisor will need to alter the system operation by overriding with manual controls or by stopping and re-teaching the system to prevent reoccurrence of the fault. An important aspect of intervention in the control of the HRC system is the capability for real-time decision-making. In complex and ambiguous situations, human operators have a relative advantage compared to robots owing to human cognitive abilities by virtue of experience. The requirement for complex event processing on the robotic side of the collaboration is an opportunity that AI can enhance. For example, Ref. [90] presents a layered architecture for HRC connected to higher-level global plant functions and supporting the use of AI tools. This framework allows for data collected at the level of an HRC work cell to train for unknown/unplanned scenarios that can be detected during operation via supervised learning algorithms that detect known categories of failure scenarios.

*3.4.6 Learn.* Finally, the sixth is that of learning which Sheridan [77] considers broadly to be the human cognitive activity of gaining knowledge from observing the results of the system's performance. Other investigators [74] have also similarly observed that as humans and robots work more collaboratively in industrial systems, a convergence and need emerges for improved teaming and integration of human actions with robot training and learning. In the telerobotic paradigm [77], teaching and learning are directed from the human supervisor to the robot. In contrast, a robot teaming model [74] is integrated with a human operator mental model by means of a Markov decision process (MDP). This work highlights how learning can extend across the collaboration space and can be bi-directional in nature. An example [89], of integrating planning, teaching, and learning into robot functions alleviates the human from these supervisory functions. In this work, a learning approach is developed based on symbolic AI (inductive logic programming, or ILP) for task execution in cognitive robots. ILP enables planning, execution, and learning framework where a set of hypotheses are constructed, updated, or discarded as the robot gains new knowledge in the form of further observations. Specifically, experiential physical learning is combined with an adaptive planning strategy so that feedback is provided to a mobile robot (in lab environment) to improve future task performance thereby robustness. Another key need in advancing HRC is being able to understand and learn the wide range of activities performed by the human operator. This ability involves being able to infer human intentions along with the myriad of complexities that this objective entails. In a very focused study [91], an algorithm is developed to model nonlinear human motions using an artificial neural network (ANN) based on position and velocity data with online learning. In Ref. [92], an RNN-based human motion trajectory predictive model parses the interaction among human body parts for more accurate trajectory prediction. Further, Monte-Carlo dropout was investigated to measure the prediction uncertainty and improve the model robustness. A broader approach [93] is developed whereby a three-pronged, integrated teaching, learning, operating strategy is adopted. This approach consists of the human first teaching the robot via natural language instructions, and thereafter, the robot learns from human assembly demonstrations via an RL algorithm. Once the teaching-learning phase is completed, this learned knowledge is used during the operation to actively assist during collaborative assembly tasks.

## 4 Artificial Intelligence For Process Monitoring, Diagnostics, Prognostics

The history of manufacturing is closely associated with the history of improving the reliability of machine equipment to reduce unexpected downtime. Research on machine condition monitoring, defect root cause diagnosis, and remaining useful life (RUL) prognosis establishes the core competence for maintenance and PHM. The goal is to enable timely detection and isolation of the precursors or incipient faults of components, predict their progression, and support rational decision-making. The significance of the maintenance and PHM system in manufacturing lies in revealing the health state of individual machines and/or the production system in real-time, providing a diagnosis of anomalies' root cause, and preventing the occurrence of a failure, all to ultimately achieve near-zero downtime [94]. Research on PHM started to take shape in the 20th century [95], with the initial focus on the physics-based understanding of the working mechanisms of machines and processes. The shift from manual to automated production in the third industrial revolution witnessed the expansion of data collection and the adoption of AI methods [95]. These methods, especially ML, can inductively learn useful data patterns and relate to processing condition and performance, with the underlying concept that data are the reflection of the physical machine characteristics. As the complexity of manufacturing processes and data continues to grow, it became evident that the traditional ML techniques, which rely on high-quality feature engineering that is subjective by nature, are inherently limited. Data in modern manufacturing, such as images for surface defect detection and sequences that underlie machine degradation, are increasingly requiring progressive, hierarchical representation which can decompose the complexity into small pieces for more effective handling [5]. The current wave of the fourth industrial revolution sees the ML landscape transformed into deep learning (DL), which leverages advanced computational infrastructure, such as cloud computing [96,97], and cascade of network layers that corresponds to different levels of abstraction of machine condition-related patterns [5], thereby improving the effectiveness of defect diagnosis and RUL estimation [11]. The classification of diagnosis and prognosis methods is illustrated in Fig. 5. The objective of this section is to present a summary of major AI techniques that have advanced the state of monitoring, diagnosis, and prognosis, which are of critical value to modern manufacturing.

### 4.1 Artificial Intelligence for Condition-Based Maintenance.

Manufacturing systems are subject to faults caused by a broad range of causes, from heat generation to corrosion and fatigue. Fault diagnosis is intended to pinpoint the source of fault generation and provide an estimate of the severity of the fault, which forms the basis for condition-based maintenance. The idea of AI-based diagnosis is to formulate the task as classification and associate the information embedded in data to the fault types and severity levels. Related research works are presented in this section.

*4.1.1 Associating Features With Faults.* ML-based fault diagnosis represents the earliest adoption of AI in manufacturing industry [98], and the success of the ML techniques is largely attributed to the good understanding of certain machine and process based on which the physics-informed features from data, such as those in time, frequency, and time-frequency domain, can be effectively extracted [11]. With good quality features, ML has demonstrated its capability in effective fault diagnosis, as reviewed in this section. The most common research area for ML-based diagnosis is rotating machinery [11].

In Ref. [99], the performance of different ML algorithms, including SVM, k-nearest neighbor (KNN), and random forest (RF), has been comparatively studied for induction motor fault diagnosis. Four different sensing signals were evaluated as input: vibration,

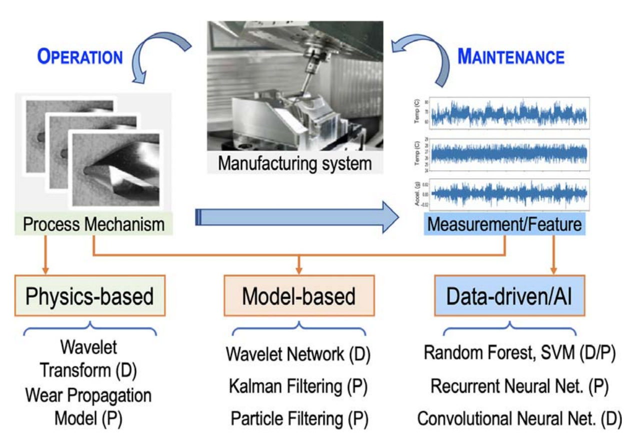


**Fig. 5 Classification of diagnosis and prognosis methods: D, diagnosis and P, prognosis.**

current, voltage, and flux. Features were extracted from time and frequency domain as well as the parameters from a statistical regression model. The results have shown that RF has the most robust performance across different types of sensing signals while SVM has the best overall fault detection accuracy. Authors in Ref. [100] reviewed Naive Bayes, KNN, and SVM for induction motor fault diagnosis based on the current sensor signal. Differing from prior work, current envelope analysis has been carried out first to reveal the amplitude-modulated nature of the motor current signal to generate candidate features. Then, the minimum redundancy maximum relevancy (mRMR) method selected the most "dominant" feature subset as input. It was shown that each technique has a different level of sensitivity to different features. The authors also confirmed that the best performance is achieved by SVM.

In Ref. [101], a novel method for bearing fault diagnosis based on visual words and sparse classifiers has been developed. The wavelet time-frequency spectra of vibration signals are first analyzed for energy-related feature extraction. Then, each signal was encoded by visual words or feature clusters, which were used as input to a sparse classifier to determine bearing fault type. The sparse classifier has also been investigated for gearbox fault severity level recognition [102]. The contribution of this work also includes a novel multi-sensor fusion method based on the covariance matrix, which allows pair-wise correlation among sensing signals to be estimated and incorporated into the analysis. In both works, the authors reported that the diagnosis accuracy from a sparse classifier is comparable to an SVM with reduced computational time. Sparse classifiers have also been investigated for wind turbine condition monitoring and fault diagnosis [103].

Beyond rotating machinery, ML techniques also contributed to improved fault recognition capability in other manufacturing equipment. In Ref. [104], faulty tonnage in a stamping machine is detected by SVM using vibration signal features extracted by a recurrent plot (RP) method. In Ref. [105], a novel method for detecting filament breakage and nozzle clogging in fused deposition modeling (FDM) has been developed, with an SVM as the condition classifier. The contribution of the work is the Bayesian Dirichlet method to effectively characterize the sensing signals.

*4.1.2 Learning Features From Data.* With increased process and data complexity, manual feature extraction becomes difficult. DNN-based ML, which allows automated learning of features specific to each task, has attracted increasing attention. Accordingly, AI-based diagnosis has evolved in the sense that (1) tasks can be increasingly customized to fit specific needs, such as simultaneous identification of fault type and fault severity level, and (2) sensing data are increasingly transformed into proper forms suitable for different NN architectures, leading to novel diagnosis concepts.

As sensing technology has continually evolved and adopted on the factory floors, image data has been increasingly gathered and analyzed for process monitoring and fault diagnosis. Compared to time-series data that has been traditionally measured, images have a higher information density and their use has been shown to be advantageous in gaining insight into the objects being monitored. How to effectively use image data has been the main research focus of DL. One of the frontier applications of image analysis is an additive manufacturing (AM), given the spatial information that is inherently embedded during the layer-by-layer printing process. Image analysis has shown to reveal critical information associated with the quality of the printed part [106]. In Ref. [107], a deep ANN model is reported to detect laser power deviation based on melt-pool images in selective laser melting (SLM). Due to the localization of the melt pool, the classification model has shown to be capable of inferring the location of potential microstructural defects of the printed part. In Ref. [108], a vision system based on deep convolutional neural network (DCNN) has been built for process fault detection in SLM. As surface textures caused by various process faults may share similar local features, higher-level abstractions are required to effectively distinguish different fault-related patterns. By using DCNN to analyze the surface textures, it has shown that the process faults can be accurately detected in a timely manner in order to avoid producing low-quality products.

Beyond images captured by vision systems, DCNNs have been increasingly extended to analyze signals that are in other forms by nature. In Ref. [109], a diagnostic system has been built to determine the gearbox fault severity level. Specifically, the 1D vibration signals were transformed into time-frequency images in order to better leverage the DCNN architecture for fault-related pattern recognition. The flowchart of this research is shown in Fig. 6. In Ref. [110], the authors reported a novel method for both bearing fault type and severity level recognition. One-dimensional vibration signals from the sensors were first converted to images using wavelet packet transform. Then, they were analyzed by DCNN for fault-related pattern recognition. Three fault types and four severity levels were evaluated using the developed method, and a near-perfect accuracy was achieved. A similar work has been reported in Ref. [111]. In Ref. [112], a 1D DCNN-based method for bearing fault diagnosis has been developed that takes advantage of the shift-invariance of the convolution operation in order to eliminate the need for time-domain signal alignment. This allows the DCNN to directly analyze the collected sensing signals, without having to rely on feature extraction or transformation to the frequency domain. More recently, researchers have begun to focus on understanding DL mechanisms with the aim of facilitating the broad acceptance of the technique. An early work has been reported for DCNN-based motor diagnosis in which the layer-wise relevance propagation (LRP) has been investigated to visualize the frequency band that the DCNN is focused on when distinguishing different motor structural faults [113].

Besides DCNNs, machine fault diagnosis based on deep belief networks (DBN) has also been reported. The main idea of DBNs is to first use the stack of restricted Boltzmann machines to progressively improve the feature discriminability. Then, the obtained features pass through a multi-layer perceptron for fault classification. In Ref. [114], a DBN has been investigated to classify bearing health conditions over the bearing lifecycle. The ant colony optimization (ACO) algorithm was investigated in order to find the optimal DBN parameters that maximize the classification accuracy.

**4.2 Artificial Intelligence-Based Prognosis for Predictive Maintenance.** Prognosis aims at predicting the temporal progression of machine performance degradation, from its current state to final functional failure. Reliable RUL estimation contributes to timely maintenance. In general, AI-based prognosis is part of the data-driven method that relies on establishing a machine performance evolution model to predict future machine performance based on its current and past status. To estimate RUL, one-step-ahead prediction is iteratively carried out until the predicted value passes a failure threshold [97]. In case that the

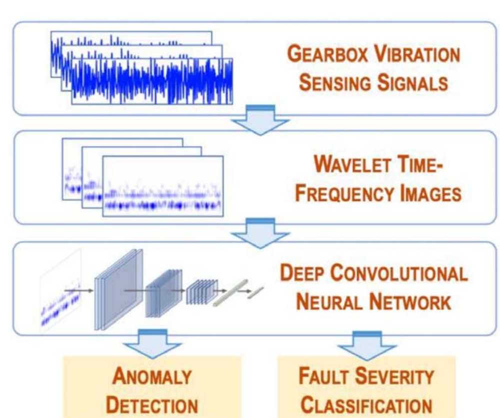


**Fig. 6 DCNN-based gearbox fault severity level diagnosis**

machine performance is difficult to measure directly, an artificial health index (HI) is often created from sensor data to represent the machine performance [115]. The HI-based prognosis and RUL estimation are illustrated in Fig. 7. Related works for AI-based machine prognosis are presented in this section.

*4.2.1 Recognizing Degradation Patterns.* Common ML techniques such as SVM and RF, although initially developed for the task of classification, can be effectively formulated as regression. By taking performance from current and past time steps as ML input, they can be associated with the future performance at output and therefore establishing the relationship underlying the machine degradation. Out of all ML techniques, SVM has been the most commonly used for machine prognosis.

In Ref. [116], SVM was investigated for bearing prognosis. The vibration, temperature, and sound sensing signals were first transformed by wavelet packet decomposition into features in the time-frequency domain. Then, an isometric feature mapping reduction technique was applied to fuse these features into HI, representing the status of the bearing. Finally, the temporal pattern among HI at different time steps was analyzed by SVM for future status prediction and RUL estimation. In Ref. [117], an SVM-based method for compressor degradation prognosis has been developed. The HI of the compressor was quantified by vibration, temperature, pressure, and moisture sensing signals, as well as the parameters of an autoregressive moving-average (ARMA) model. The HI sequence was then analyzed by SVM to predict future progression of compressor performance. A similar work has been reported for lithium-ion battery prognosis in which the loss of rated capacity was used as the HI of battery, with SVM as the ML technique [118].

In contrast to the aforementioned works in which an evolution model is first constructed to reveal the temporal relationship among machine performance at different time steps and subsequently, leveraged to predict future performance and estimate RUL, other researchers have investigated the method of directly associating current/past performance to RUL. In Ref. [119], an SVM has been investigated for direct RUL estimation of aircraft engine based on sensing signal features from current and past time steps and therefore, bypassing the steps of generating HI. In Ref. [115], an ensemble RUL estimation method has been developed for induction motor prognosis. During the operation, 13 channels of signals from seven sensors were collected, representing voltage, current, vibration, load, speed, temperature, and sound. Five single-layer NNs with different initialization constitutes the ensemble algorithms. A similar work based has been reported for aircraft engine performance prognosis in Ref. [120], in which the ensemble algorithms involve an SVM, a relevance vector machine (RVM), an exponential model, and a quadratic model. To adaptively weigh the contribution from each algorithm, an optimization-based fusion method has been developed and shown to be able to improve the estimation accuracy and robustness.

*4.2.2 Analyzing Degradation Patterns.* When the relationship among degradation time steps becomes too complex to be characterized by a single regression model, traditional ML techniques become ineffective. In such scenarios, the NN architectures, especially RNN and its variant long short-term memory (LSTM), offer several advantages in comparison: (1) they can explicitly model the inner relationship among machine performance at different time steps; (2) they can decompose the complex temporal patterns into a series of simple components which, individually, can be approximated by a single regression at each network layer, before being assembled to fully describe the degradation trend. These advantages have made RNN/LSTM an attractive option for machine prognosis. The research highlights are presented as follows.

In Ref. [121], an RNN-based bearing prognosis method has been developed. Vibration signals from a defective rolling bearing were transformed using continuous wavelet transform. Statistical parameters computed from both the raw data and the pre-processed data were then utilized as candidate inputs to an RNN. Analysis has shown that the developed method is accurate in predicting bearing defect progression. In Ref. [122], a bi-directional LSTM for aircraft engine RUL estimation has been developed. The HI is constructed by a single-layer NN which fuses the on-board sensing signals to represent the engine performance. The bi-directional LSTM allows the information to flow forward for prediction and backward for disturbance smoothing. The developed method has shown to improve RUL prediction accuracy as compared to uni-directional LSTM and traditional ML techniques such as SVM. A similar work has been reported in Ref. [123] in which improved RUL estimation for the lithium-ion battery has been achieved using the LSTM-based approach. Specifically, the Monte Carlo method has been investigated to construct an ensemble of LSTMs, in contrast to using one single LSTM. This approach allows the RUL estimation to be displayed as a probability distribution, rather than a deterministic value. Furthermore, it has shown to be more robust under noisy sensing signals. In addition to revealing degradation patterns, LSTM has also been investigated to model the relationship between sensing signals and machine performance for HI construction. Related works have been reported in Ref. [124].

Recently, LSTMs have also been investigated in conjunction with model-based techniques, such as particle filters (PF), in order to alleviate the limitation of insufficient observations for degradation model parameter estimation. PFs have been widely studied for the prognosis of complex engineering systems such as HVAC [125] and aircraft engines [126] in which the degradation model can be continuously fine-tuned by the incoming sensing observations based on Bayesian inference. In Ref. [127], an integrated method has been developed for fuel cell RUL estimation. For an on-going degradation sequence, an LSTM trained on historical data was leveraged to provide degradation path forecast, beyond what has been observed from the actual fuel cell. These additional forecast data help PFs more accurately estimate the degradation model parameters, leading to improved estimation accuracy.

As computational capability and infrastructure continue to advance, it can be expected that advanced AI algorithms will continue to emerge in the era of the fourth Industrial Revolution. Prior research in this area has established a solid foundation for further advancement toward the realization of smart manufacturing.

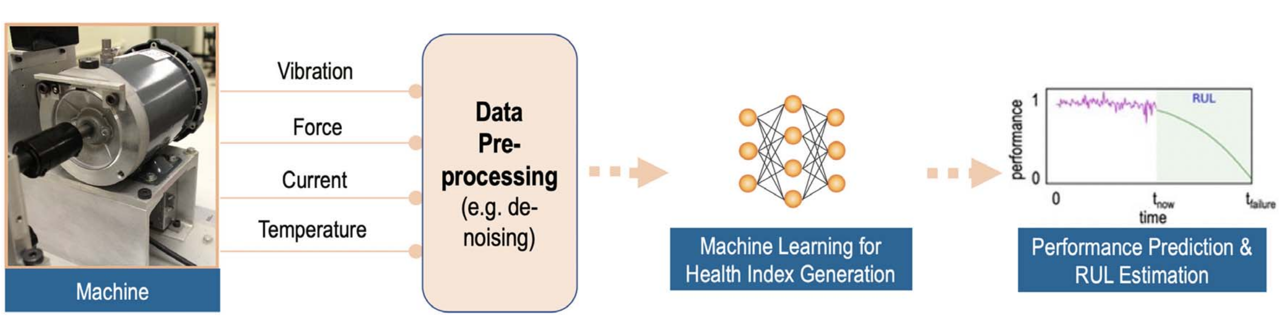


**Fig. 7 HI-based machine prognosis and RUL estimation**

## 5 Artificial Intelligence for Manufacturing Process Control

This last section deals with the lower levels of the manufacturing system hierarchy, namely, the machine/equipment level as it extends into the material level domain. While the previous section treated the condition and state of the machine/process as it relates to reducing equipment failures, this section focuses on modeling and control of the process to achieve desired process quality under the assumption that equipment failures are not causing quality issues. Furthermore, this section specifically explores the role AI techniques can provide to significantly increase understanding of the material-to-process relationship as an important new opportunity for enhanced process control, efficiency, quality, and productivity [128,129]. The impact of an improved understanding of this relationship spans the classical manufacturing process control and materials processing communities. The former is provided with newfound variables and means to better optimize process control and the latter will be potentially dramatically changed in the context of designing new materials and materials processing to more directly optimize downstream manufacturing processes.

**5.1 Artificial Intelligence for Modeling and Control of Manufacturing Processes.** To date, the initial AI techniques that have been applied in manufacturing process control have been focused on applications where there are limited formal or analytical models due to their complexity or the resource-intensive computations required to develop tunable process controllers. However, as with other areas in the factory, the increasing amount of instrumentation and the ability to collect large amounts of data along with the ability to extract necessary process signals and features will continue to facilitate these types of applications which do not require an accurate mathematical model nor formal physics-based simulation of the system [130–134]. A survey of traditional manufacturing processes such as machining, joining, stamping, and molding indicate this type of benefit may be obtained by using AI techniques such as SVM, RF, DNN, and genetic algorithms [135–139].

*5.1.1 Artificial Intelligence for Modeling and Optimization of Manufacturing Processes.* An overarching objective of implementing an AI tool in manufacturing process control is to produce high-quality parts cost-effectively [140]. The implication is that critical process parameters need to be captured in the ML model. For example, a laser manufacturing study [141] used an ANN with parameters pertaining to laser power, cutting speed, and pulse frequency which was critical model factors in determining process success. In order to optimize these parameters, the ANN was developed to predict laser cutting quality expressed as explicit non-linear functions. The results demonstrated that the ANN successfully determined a set of parameters that best optimized the quality of the cutting process and predicted outputs based on given inputs to the laser.

In other applications of AI to metal cutting, specifically milling process control [142,143], the use of predictive modeling is beneficial in two ways. The first being the improvement of process efficiencies [144]. This encompasses maintaining a real-time knowledge of the current mill conditions and creating a stable environment for the tool, thus increasing tool life. In conventional milling processes, a major task is to ensure desired surface roughness which is a parameter that normally degrades with increased tool wear. Typically, routine tool schedules change worn cutting inserts before a given surface quality threshold is exceeded [145]. A variety of ML tools have been used to model predictions in surface roughness changes. In this manner, tool wear and supplier power can be considered based on surface roughness deviations. The other major improvement from ML practices is the prediction of wear time. Process control via ML can then proactively adjust the process parameters to increase its life span. Notably from the data perspective, ML requires a large database to account for different combinations of tooling parameters. This enables tool life modeling using the ANN to accurately predict future wear [144].

*5.1.2 Artificial Intelligence for Online Control of Manufacturing Processes.* Manufacturing processes are generally multivariable and time-varying by nature. As an example, grinding is highly nonlinear and its multi-modal relationships are difficult to be defined accurately via mathematical equations since output variables are not only dependent on input variables but also dependent on other output or intermediate variables. Furthermore, most existing analytical models for complex grinding processes are rather limited and can only describe partial relationships between design (control) variables and process (output) variables, while all the parameters must be considered simultaneously for optimal operation of such processes. In such cases, online process control faces a major challenge. Conventional feedback control or optimization techniques encounter severe limitations in dealing with such problems. Because of these difficulties, when a new process must be designed or an existing process must be controlled, an engineer attempts to utilize all other available resources besides analytical models, such as expert knowledge, experimental data, handbooks, and vendor information. Even if pertinent information is available, integrating all the heterogeneous information and designing an optimal condition is not an easy task, often requiring a long lead time and much trial-and-error experimentation. In view of the complex nature of the grinding process and stringent finish, accuracy, and part surface integrity requirements, the current practice of designing or controlling grinding processes leave an opportunity for improvement using more robust approaches. This has led to the development of an "intelligent" approach to online control of the grinding processes [146,147] and other strategies that use AI-based controllers based on grinding forces or other in process data such as tooling deflection.

**5.2 Modeling the Effect of Manufacturing Conditions on Material Property.** One of the challenges faced in manufacturing processes is determining what parameters to adjust and what are the levels to adjust. The selection of these parameters can be a major contributing factor to the quality of the final manufactured parts. The ability to collect a vast amount of data on these changes can help in increasing efficiency and quality [148,149]. AI has been successfully implemented when there is a large pool of data to be trained on. When enough of these data points are collected, they can be used as a data-driven way to predict properties and results of experiments in a fraction of the time. AI's applications can be applied to both macroscopic and microscopic properties for prediction, covering the whole spectrum of possibilities. For example, the properties of materials, such as hardness, melting point, and molecular atomization energy, can be classified and described at either the macroscopic or microscopic level [150]. In most cases when the macroscopic performance of materials is studied, the focal point is geared toward the structure-performance relationship [151]. AI applications in microscopic property prediction can concentrate on several aspects, including and are not limited to the microstructure, the lattice constant, electron affinity, and molecular atomization energy [150,152–155]. Material's microstructure can be characterized through image data such as scanning electron microscope (SEM) as well as transmission electron microscope (TEM).

## 6 Challenges and Opportunities for Future Research

Factories are getting smarter as companies are increasingly able to leverage AI to transform information from various aspects of the manufacturing system into actionable insights. However, many gaps still exist that should be addressed to ensure that AI can be seamlessly integrated into factory operations. Five related topics are summarized here as recommendations for future research.

**6.1 System-Level Analysis.** ML has seen increasing utilization across all levels of the manufacturing system hierarchy. However, compared with the successes of ML in specific applications of process monitoring, optimization, and PHM, utilization is limited at the system level of decision-making [68]. This is primarily attributable to the stochastic and non-linear dynamical nature of manufacturing systems and the complex multi-stage processes and dependencies among vast amounts of heterogeneous data generated therein. Furthermore, although the general advantages of ML lie in its ability to handle NP-complete problems, typical of intelligent optimization problems, the appropriate selection of techniques and algorithms remains challenging. An in-depth understanding of a problem, its causes, consequences, and desired solution state must be known or well investigated to improve the likelihood of effective AI tool selection and subsequent model building, data analysis, and interpretation. These matters all deal with the need to have adequate domain expertise during the problem definition phase which is vital to ensure that all aspects of the problem are well understood and no key data or assumption is overlooked. Additionally, at the highest level in the manufacturing hierarchy, there is a variety of interacting plant control systems that govern overall plant performance. Though single ML approaches have been developed, no single AI tool or even suite of tools have yet to integrate and bridge all of the performance objectives of these control systems. RL has been suggested as an approach. However, practical difficulties to train an RL algorithm in a real operating system where productivity cannot be jeopardized remain a challenge.

**6.2 Data Quality.** The increasing availability of heterogeneous data in manufacturing systems presents new challenges. First, the data can contain a high degree of irrelevant and redundant information while the relevant part may be missing. These data curation issues present a challenge for the application of ML algorithms as the availability and quality of the manufacturing data have a strong influence on the performance and suitability of AI algorithms relative to expected results. Second, the quality of any knowledge generated from data analysis depends on the context developed when collecting and managing the data itself. Given the variety of viewpoints in production, it is critical that data collection and management approaches support multiple viewpoints for different applications by dynamically linking different data, information, and models [156]. One future opportunity associated with improved data quality is to converge local correlation-based predictions (e.g., machine tool health status and individual process status) to facilitate a causal understanding of the dynamic and complex manufacturing operations in a factory. As described in Fig. 2, any system-level decision-making and control can be traced to individual process-level control action, and any process-level optimization or parameter changes can be examined for its real impact on the entire connected system. Therefore, ensuring the quality of local data is the key to enable a causal analysis of the manufacturing system.

**6.3 Transfer Learning and Data Synthesis.** While various AI techniques have demonstrated the capability to accurately model and optimize system performance, interpret human motion to realize human–robot collaboration, detect and classify defect and predict future machine condition, research published so far has been largely built upon the assumption that sufficient data are available for model training and validation. However, in real applications, obtaining data from different operating conditions or manufacturing configurations in a systematic fashion is often times infeasible, since data collection that encompasses all possible scenarios is financially and operationally prohibitive. Furthermore, data exchange/accessibility through public/private networks can be restricted due to security concerns. Two approaches have been investigated in the scientific community to overcome these challenges: transfer learning and data synthesis.

Transfer learning includes a series of techniques to adapt a model that has been well established in a source domain in which training data are sufficient, to a related, target domain in which data is scarce. For condition monitoring and fault diagnosis/prognosis, the most noted advantage of transfer learning is to allow experimental data obtained from machines without faulty conditions for model construction on real production lines when faculty conditions may occur [157]. Reported research on this topic this field can be characterized into three categories: (1) model transfer among different working conditions [158,159], (2) model transfer among different machines [160], and (3) model transfer among different fault locations or types [161]. Further examples of transfer learning include human action recognition [162] for human–robot collaboration in assembly. These examples illustrate that, through the proper transformation that corresponds to the specific manufacturing scenarios, transfer learning can address model scalability, opening up the possibility of establishing a general rather than a limited solution to a specific manufacturing aspect. On the other hand, it is noted that transfer learning at the current stage is still limited to trial-and-error, ad-hoc approaches. More rigorous theoretical research on the topics such as transferability of data remains essential to facilitating the broad applicability and acceptance of transfer learning-based techniques.

Data synthesis refers to generating synthetic data that highly resembles the real data by sufficiently learning data characteristics, which allows us to bypass the limitation of data availability. Traditionally, data synthesis often relies on interpolation (e.g., Synthetic Minority Over-sampling Technique or SMOTE), which cannot capture complex data characteristics [163]. A major breakthrough came with Generative Adversarial Networks (GAN) [164], a DL method that is able to learn salient features and synthesize data with high fidelity. The basic concept of GAN is a competition between a generator, which analyzes real data to produce synthetic ones, and a discriminator, which distinguishes the synthetic data from real ones. These two are trained iteratively to improve the capability of each. The final result is an equilibrium state, resulting in a synthesis of the manufacturing data with high-fidelity. Early works of GAN implementation have been reported. For example, Ref. [165] investigated using synthetic vibration signals to establish the gearbox fault diagnostic model. Spectral analysis has shown that the synthetic data effectively captured the fault-related signal features, such as the characteristic frequencies. As with other DL techniques, a deeper analysis of the theories related to GAN remains essential to fully establishing the technique as a viable solution to the issue of data limitation.

**6.4 Modeling Material-Processing-Property Relationships.** To ensure the desired performance of the final manufactured parts, a comprehensive understanding of the material-processing-property relationship is required. Conventional modeling and control schemes have been developed and applied to achieve manufacturing performance in the presence of variations in process dynamics and unpredicted uncertainties. However, these controls are usually difficult to design and computationally intensive when the processes are highly nonlinear. In addition, automatically updating the necessary parameters from the modeled process remains a challenge. Furthermore, a priori information on the structure of the process dynamics and model uncertainty bounds is usually unavailable. In such cases, AI techniques have the potential to avoid the complexity of modeling the complete material-processing-property relationship for improving prediction accuracy and thus productivity in a variety of manufacturing processes.

**6.5 Promoting Trust in Artificial Intelligence.** As AI continues to evolve and advance, understanding and interpreting the output of AI tools and related technical details become increasingly exclusive to data scientists and similar professionals with specialized skills in this domain. Often times, this creates a knowledge gap leaving plant managers and production engineers lacking this background with the ability to comprehend and appropriately interpret the meaning of the results from AI models in a manner consistent with the context of the problem area. This highlights a significant challenge of AI in manufacturing, namely the importance of proper interpretation of AI analysis to decision-makers who may not be experts in AI. Without a proper grasp of the analysis that relates to the fundamental physics, users would have no basis to trust and accept the analysis results. Since manufacturing operations are based on what is known physically, not on what might probabilistically occur as indicated by AI models, more transparent, physics-guided process models are required. This has given rise to research into explainable AI models, commonly referred to as XAI, which facilitates mental-support models to assist users of AI technologies more readily adopt them as powerful tools to enable "smart" manufacturing. As AI research continues to evolve, it can be expected that the topic of trust in AI will assume an increasingly important role and attract more intense research activities.

**6.6 Practical Implementation of Artificial Intelligence in Manufacturing.** While the majority of the AI research in manufacturing has been conducted in a laboratory environment (such as using test rigs), companies have begun to adapt and implement the state-of-the-art into daily operations to improve production efficiency, flexibility, and reduce cost. As an example, a technical report published in 2018 [166] described the implementation of DCNN as a machine vision solution to facilitate early detection and classification of defects, such as epoxy staining and excursion related to ball application, in a wafer production line. The system consists of a classification inference cluster to support large-scale production and a model-building unit that builds and refines the DCNN model. During wafer production, when the DCNN result does not meet the required confidence level, which is specified per individual production stages, the wafer unit is transferred to manual classification, which in turn allows to augment the existing training data and continuously improves the DCNN accuracy and robustness. It is reported that the system can now automatically and accurately detect and classify any defect that would otherwise require a manual procedure, and is able to reduce about 80% of total workers' time.

In Ref. [167], a novel vision-based system is developed for fabric texture identification and implemented in a company that produces automotive interior parts. In an industrial environment, the unstable ambient illumination poses considerable challenges in applying existing image classification techniques. The images captured in unstable lighting conditions are pre-processed with Laws and Sobel filters to extract features, which are then fed to an SVM classifier enhanced by pyramid analysis. The proposed technique reaches a texture classification accuracy of 98% while satisfying the computation time requirements in a massive production setting.

It is important to note that more effort is needed to promote AI from the perspective of the industry and facilitate the broad acceptance of AI techniques.

## 7 Conclusions

In this work, we have broadly reviewed the current use of AI and its potential for further opportunities in manufacturing systems and processes across multiple hierarchical levels. The survey of the literature showed that a wide array of AI tools has already been implemented to address a diverse set of problems throughout a plant hierarchy. However, despite this widespread use, there have been varying degrees of success and corresponding challenges that have been identified in implementing these tools. For example, supervised learning in manufacturing system control benefits from the high richness of labeled data, yet the problem is knowledge-sparse. Simulation of manufacturing systems is a path to knowledge through the ease by which training data may be generated. However, this is limited by the model's ability to reflect reality with a high fidelity. In the area of HRC, many AI technologies are being used to successfully aid in the communication of intent between human and robot, based on voice, gesture, gaze, and explicit commands. On the other hand, a higher cognition level of interactions focused on shared workpiece activities still requires further research to develop robots with reliable mental models of their human counterpart to dynamically generate the corresponding motion-adaptive to human behavior.

In regard to process monitoring, diagnostics, and prognostics, the deployment of AI tools has been more extensive owing to the rich stream of data emanating from processes, sensors, and equipment. Conventional ML methods rely on high-quality data to extract relevant features. Thus, AI-based diagnosis has found popular usage to formulate classifications and associate data to corresponding fault types and severity levels.

This work also examined the research into the application of AI to facilitate improved understanding of material properties as used in manufacturing process monitoring and modeling. For example, AI has been used to predict material properties and experimental results in a fraction of the time that would otherwise be spent via conventional methods. Such prediction of material properties applies to both macro and micro levels wherein properties such as hardness, the melting point can be represented through simulation, providing valuable input to complex modeling of processes that use highly time-dependent material properties.

The four domains summarized above also point to the new challenges and opportunities for future research, as identified in the area of system-level analysis, data quality, model and knowledge transfer, modeling material-processing-property relationships, and interpretation of results based on AI techniques. Despite the varying degrees of applicability and research gaps that exist and need to be overcome in each of the four domains, the trend is undeniably one of the increased implementation of AI-based analytical tools. That there remain significant data, and problem formulation challenges to be solved does not limit the already demonstrated opportunity for AI to transform manufacturing as we know it today.


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## Conflict of Interest

There are no conflicts of interest.

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