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Human in the Loop: Industry 4.0 Technologies and Scenarios for Worker Mediation of Automated Manufacturing

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ABSTRACT Industry 4.0 derived technologies have the potential to enable a new wave of digital manufacturing solutions for semi and fully automated production. In addition, this paradigm encompasses the use of communication technologies to transmit data to processing stations as well as the utilization of cloud based computational resources for data mining. Despite the rise in automation, future manufacturing systems will initially still require humans in the loop to provide supervisory level mediation for even the most autonomous production scenarios. Through a structured review, this paper details a number of key technologies that are most likely to shape this future and describes a range of scenarios for their use in delivering human mediated automated and autonomous production. This paper argues that in all cases of future manufacturing management it is key that the human has oversight of critical information flows and remains an active participant in the delivery of the next generation of production systems.

INDEX TERMS Human computer interaction, intelligent systems, visualization, interactive systems, context awareness.

I. INTRODUCTION

Recent advances in technology have enabled the possibility of Industry 4.0 and the digitization of manufacturing systems. Through the use of miniature and ubiquitous sensors, Industry 4.0 offers the ability to collect data at source in real-time. In addition, this paradigm encompasses the use of communication technologies to transmit data to processing stations, robotics as well as the utilization of cloud based computational resources for data mining [1]. For the first time in the history of Manufacturing, we now have the ability to collect data from manufacturing systems spanning the globe, simultaneously linking together production systems [2], [3]. As a result of this connectivity components in supply chains can be linked, analyzed and optimized for overall performance. In this work, nascent technologies are discussed that could be applied towards building more flexible and resilient supply chains for manufacturing. This discussion is particularly pertinent in forming a response to the recent COVID-19 pandemic where manufacturing ground to a halt in order to stem the spread of the virus. In this paper discussion is made of technologies that could ensure that future manufacturing systems are flexible, resilient and robust to disruptions [4]. Such manufacturing systems would also be supported by business models that are resistant to disruptions.

From the review of literature conducted in this research it is the case that, despite the rise in automation in the near to mid future, manufacturing systems will still require humans in the loop to provide supervisory level mediation for even the most autonomous implementations. This is supported by [1], [5] in which the authors highlighted the potential for Industry 4.0 technologies to enhance human-machine integration in manufacturing systems as well as augment the physical and cognitive capabilities of workers within them [5].

Nevertheless, [6] discuss the challenges that human in the loop digitalization presents including the provision of technological support for humans. They also discuss how adding knowledge to manufacturing equipment (Intellect), improving collaboration between humans and manufacturing equipment (interaction) as well as how humans could exploit the intelligence of technologies for better communications with manufacturing equipment (interface) should be taken

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into consideration for the adoption of smart technologies towards the smart manufacturing vision. In [1], this argument is taken further in which they present a social human in the loop cyber physical production system architecture. In their context, they propose that the understanding of human roles from a social perspective is important in designing efficient manufacturing systems of the future. This perspective becomes even more important when the human agent is located in a heterogeneous ecosystem of other intelligent agents [7]. In this scenario, human factors consideration becomes important and necessary in order to ensure that humans are kept safe. The heterogeneous nature of the ecosystem does present some dynamic multi-level challenges that need to be addressed [7], [8].

In the state-of-the-art papers presented above, we discover that there is still a need to discuss why a human will still be needed in the loop of future manufacturing systems as well as in what capacity. How will the humans interact with all the technologies, such as collaborative robotics, swarm robotics, explainable artificial intelligence, intelligent visualizations and many other nascent technologies, that are increasingly present in these manufacturing systems? What will be the human's role?.

In order to set the stage to answer this question, we must start with what a manufacturing system is, the reason why it exists and what has been driving the evolution of manufacturing systems from the earliest of human civilization to present day. By discussing traditional manufacturing systems that have signified shifts in manufacturing paradigms, we aim to set the background for the rest of this manuscript. Since a majority of manufacturing enterprises still make use of these traditional manufacturing systems in one form or the other, we also discuss the potential for introducing the human in the loop concept into them as shown in Table 1.

Despite advances in technology, a manufacturing system remains a collection of labor resources and integrated equipment, utilized to process and assemble raw production materials [9]. Nevertheless, as seen in Fig. 1, the need for bespoke goods is one of the many factors driving the evolution of manufacturing systems as well as the aim to create more volume per variant when market disruptions happen or customer tastes change. Job shops and project shops were the earliest type of manufacturing systems used to meet these challenges. The project shop is intended for the manufacture of large-scale products which require multiple components in one location. Project shops were used to develop many monumental structures of the human civilization, such as the Egyptian pyramids and modern-day civil engineering projects such as bridges [12]. Towards the introduction of automation in project shops, Bauda *et al.* [13] proposed 'Air-Cobot robot' for visual inspection of production quality. The Cobot is a form of Collaborative Robot (Cobot) capable of assisting humans performing, often, manual physical tasks. In this way Cobots enhance human actions and/or decision-making capabilities rather than seeking to replicate such inputs in fully automated implementations.

TABLE 1. Manufacturing system.

Manufacturing system	Features	Potential Cobot usage
Cellular manufacturing	High product variation and highly skilled labor	Task-based HRC to improve efficiency
Flexible manufacturing	High product variation and highly skilled labor	Intelligent assist system for the variate product
Flow Shop	Low product variation and low skilled labor	Solving scheduling problem and manual labor shortage
Reconfigurable manufacturing	Customized flexibility and adaptability	Reconfigurable machine tool
Project shop	large products and low variation	Air-Cobot for vision inspecting
Job Shop	High product variation with highly skilled labor	Packaging of goods

Job shops systems were used to develop bespoke goods for individual customers. They rely mainly on manual labor and as a result, are limited in the volume that they can produce. These are still in use today in various manufacturing enterprises. A flow shop is a step up from job shops and takes the form of a product-oriented system with an inherently complex scheduling system that is often required for optimal order sequencing. The setup of the flow shop supports an increase in the volume of goods produced but with very low variability allowed in the product types. Nevertheless, scheduling is a challenge especially when there are many product varieties passing through the system. Sadik and Urban [14] introduced a case study which optimizes the scheduling problem with Human-Robot-Collaboration (HRC). Cellular manufacturing which groups similar parts into families and assigns the associated machines located in each cell into groups [15] is used to implement small scale production, often requiring just a single supervisory worker [16]. The inherent people-oriented nature enables the human operator's versatility and flexibility. However, to improve production efficiency, robot assistance could be added into the system as the next step.

Flexible Manufacturing System (FMS) is defined as a production method which is adaptable for production type and size. Kruger *et al.* [17] proposed Intelligent Assist Systems for more flexible assembly tasks. The Reconfigurable Manufacturing System (RMS), combining the flexibility of FMS with the high throughput of a dedicated manufacturing system, is designed to adapt to rapid market changes within the same part family. Though manufacturing systems such as Flexible and Reconfigurable manufacturing systems support the push for bespoke goods (through flexibility and adaptability), there are still challenges in increasing the volume of goods produced in each variant through automation. This

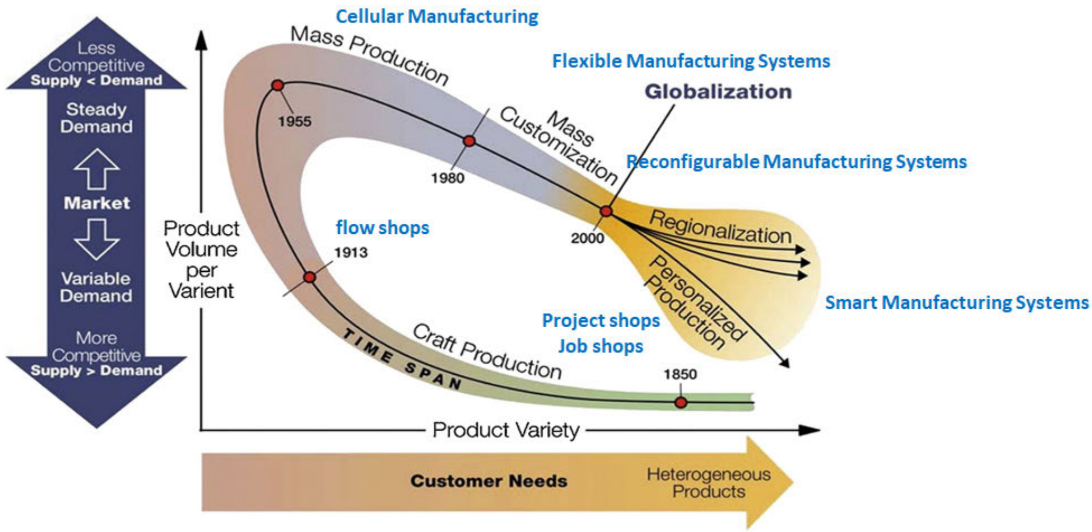

FIGURE 1. Evolution of manufacturing paradigm shifts. Adapted from Koren [10] and modifications of Lu *et al.* [11].

challenge is especially true for Small Medium Sized Enterprises that are in the supply chain of Large Enterprises in the Automotive or Aerospace sectors. One of the reasons for this challenge is the complexity of these systems and the high level of expertise required to make use of them. As a result, the application of AI and simulation concepts as well as how to make use of the general flexibility offered by human labor (through the concept of human in the loop) in the next generation of manufacturing systems is increasingly being investigated by researchers. This gap and the need for this discussion is the focus of this research.

In the next section, we discuss the methodology and structured literature review informing this research as well as the research questions we aim to answer. Subsequently the paper is then divided into the following sections: Automated and autonomous manufacturing; Explainable artificial intelligence; Audit trails for manufacturing; Context aware computing; Visualization and interaction; Collaborative robotics; Internet of things intelligence at the edge; Next generation manufacturing management. The paper then puts forward 5 scenarios for next generation production systems. A section detailing the research gaps remaining that need to be addressed for the achievement of the 5 scenarios put forward paper is then followed by a summary of the main conclusions drawn from this research.

II. METHODOLGY AND STRUCTURED LITERATURE REVIEW

This work follows a structured review process in which an evaluation of existing research literature is carried out in order to address formulated research questions. The initial questions that this research set out to explore and investigate focuses on the roles that humans can and should play in the decision-making process and oversight of automated (and even autonomous) systems. Research questions posed were:

RQ1: Why might the human still have a role? In [1], the authors discuss how humans might be kept in the center of a social human-in-the-loop cyber-physical production system. In this paper, we ask why might humans still have a role in a smart manufacturing system and is it necessary? Surely, with advances in technology, collaborative robotics and other industry 4.0 technologies, human roles should be potentially limited or at the extreme end removed all together. This should lead to manufacturing systems that do not need the environmental comforts (safety, temperature, lights) that typical humans need thereby resulting in a term called 'lights out' manufacturing. In fact, without humans, environments could be better tailored to suit the needs of equipment or the manufacturing conditions optimal to the creation of a product (e.g. some 3D welding systems require inert gas environments). This leads us to the next research question that we posed.

RQ2: Are there limits to 'lights out' manufacturing? In lights out manufacturing, the entire manufacturing process is conducted entirely by robots with humans feeding raw materials at the entrance of the factory and collecting manufactured products at the exit [18]. This approach should potentially increase the efficiency of a plant by increasing the operational time of the plant as well as reducing the deficiency in the parts. However, what is the limit to this approach and under what conditions does the manufacturing system fail to meet up with expectations? As a result,

RQ3: is the 'Human in the loop' concept not just necessary, but a desirable end goal for research activities involving automated manufacturing?.

In the completion of this structured review of literature, a number of search terms were used for the identification of relevant papers (as shown in Table 2). The search terms were derived from an initial review of the current topics in manufacturing automation. This was then focused to the topics

TABLE 2. **Structured literature review: search terms and papers.**

Search Term	Peak Year	Published in 2020	Total
Automated Manufacturing	(2020) 1178	1178	12,325
Autonomous Manufacturing	(2019) 442	396	3457
Explainable AI and Industry	(2020) 36	36	68
Audit Trail and Manufacturing	(2003) 6	3	40
Context Aware Computing	(2011) 533	450	8364
Context Aware Computing and Industry	(2020) 32	32	262
Collaborative Robotics	(2020) 611	611	3840
Manufacturing and Swarms	(2020) 238	238	1825

seen as most relevant by the authors and informed by literature. Subject areas such as Explainable Artificial Intelligence (XAI) and Collaborative Robotics have been included as they are seen by the authors and recent research works as having particular pertinence for the development of automated manufacturing systems with the possibility to include human inputs and oversight. Distinction is made between context aware computing in general (where additional metadata concerning the operational context or environment is provided to an algorithm) and specific industrial (non-services based) uses of this subject area. The publication database consulted was Scopus with relevant papers indexed between 2000 and 2021. In addition, the Web of Science and Scholar databases were used as comparators to identify additional works not found by Scopus. Table 2 shows the search terms and the peak paper publishing year followed by the number of publications in 2020.

For areas that brought back over 1000 papers the 'PRE/' term was used with a combination of 0 to 10 intervening words allowed between the searched for terms (to ensure the two search terms were found in contiguous fashion); with collaborative robotics the paper total was reduced to 153 with no intervening words. This first filtering of the papers helped to establish which works were most relevant to the questions posed in this study and reduced the considered paper total to 868. A second stage involved further filtering with additional attention given to papers that were more likely to contribute to the development of the scenarios for Human mediated technology adoption in manufacturing proposed by the authors. It was also the case that additional weighting was given to more recent papers (post 2015 publication date) leading to a predominance of such works in the completed

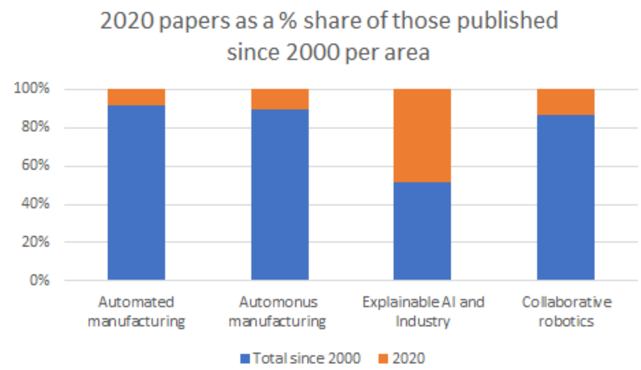

FIGURE 2. **2020 papers as a % share of those published since 2000 per area.**

review. As can be seen in Fig 2. certain subject areas contain a higher proportion of recently published papers than others. This stage involved the rapid analysis of abstract, introduction and conclusions (including findings and future research) for each paper. This second stage reduced the overall total amount of papers to 190. The final stage of the literature review commenced with the full reading of the remaining papers reducing the total to just over 100 relevant works for inclusion. At this stage, in depth analysis of the remaining papers involved an assessment of the contribution and relevance of the publication and its impact factor rating (as rated by Clarivate).

In the next section a brief overview of traditional manufacturing systems is provided, along their features and capabilities.

III. AUTOMATED AND AUTONOMOUS MANUFACTURING

Research involving machine learning in relation to manufacturing activities has achieved a mantuary measurable in decades, and it is now the case that such software systems are capable of lending real-time decision-making capability to implementations of shop floor automation.

Jeken *et al.* [19] describe an approach for autonomous production involving intelligent parts that cooperate with the production system to independently form products and fulfill orders. The approach of [19] also utilized hybrid simulation to model how the autonomous objects would interact and to study the effect of multiple product variants. The autonomous products in [19] were generic in nature and took the form of conceptual entities within the simulation model. The research of Li *et al.* [20] suggest the extension of the software agent swam approach to that of product design and multi organization R&D projects, citing these directions as key uses of AI in the development of future manufacturing scenarios. The notion of intelligent objects in manufacturing has also been explored in earlier work by Pille [21] who experiment with RFID transponders embedded in die cast automotive parts with the aim of establishing their use as in- process health monitoring sensors.

The smart factory concept is one envisaged, in part, as a response to the increasing availability of automation technology that incorporates or is linked to machine intelligence driven control systems within the overarching theme of smart manufacturing.

Suginouchi *et al.* [22] explore the possibility for customer-co creation, where a customer's needs are directly input into an equation number in parentheses. In utilizing 3D printing [23] explore a CPS (Cyber Physical System) approach to the production of shoes for individual customers.

In their review of smart manufacturing reference architectures Moghaddam *et al.* [24] seek to provide an overall blueprint, in part, for the smart factory. In this work [24] make the point that manufacturing may be broken down into a set of micro services, described by metadata enhanced communication services such as OPC-UA and AutomationML. In addition, according to [24] smart or intelligent object research in manufacturing has focused on communication between such entities with little research on how they interact with each other or how humans interact with such systems. Kusiak [25] describes six pillars of smart manufacturing as: manufacturing technology and processes; materials; data; predictive engineering; sustainability; resource sharing and networking. Kusiak [25] underlines not just the importance of data to smart manufacturing but the need to employ the latest visualization methods, such as provided by mixed reality technologies, and predictive capabilities. In the words of Lu *et al.* [26], smart manufacturing is: "fully-integrated, collaborative and responsive operations that respond in real-time to meet changing demands and conditions in the factory, in the supply network, and in customer needs via data-driven understanding, reasoning, planning, and execution of all aspects of manufacturing processes, facilitated by the pervasive use of advanced sensing, modeling, simulation, and analytics technologies."

The need to simulate and replicate the smart production environment in digital form is an area described by Lu *et al.* [26]. Such digital twin implementations are in the opinion of [26] required due to the nature of smart manufacturing where real time decisions can be made at any point in the production process by intelligent systems (the digital twin concept will be explored in section VII of this paper).

An interesting development concerning scheduling in manufacturing utilizing IoT sensing is illustrated in the work of Wan *et al.* [27] who propose the use of semantics in the communications utilized in the layers of the proposed system. The 'Ontology-Based Dynamic Resource Management' framework of [27] also features software agents and provides an avenue for expansion so that humans can potentially interrogate and understand the decisions made by the system through use of natural language.

Lights-out manufacturing is a term that describes a fully automated production facility operated though computer control and without the need for human intervention [28] In earlier work Brann [28] detail a study into the provision of an autonomous control system for the operation of satellites by NASA. The study of [28] found that the automated system in place did require a significant amount of human interventions in order to function correctly; it was also found the inspection of lower level tasks was not possible, in effect the decision making was not visible or readily explainable to human operators. Lee [29] make the point that while the move to lights out factories has advanced over recent years there are still requirements for human input and, as will be discussed in more detail in a later section of this paper, much scope still exists for more advanced forms of automation and in particular human robot collaboration.

IV. EXPLAINABLE ARTIFICIAL INTELLIGENCE

The field of Explainable Artificial Intelligence (XAI) has seen a growth in interest in recent years. Increasingly there is a need for systems employing machine intelligence and learning techniques to provide explanations in order to justify the trust Humans are required to invest in such software-based entities. This has led to a spectrum of research projects whose central approach ranges from parameter and feature tagging to the schematic modelling of human reasoning.

Magariño *et al.* [30] emphasize the potential utility of explainable AI in its use in establishing and maintaining Human trust in IoT based systems. The authors [30] go on to outline an approach based on deep learning capable of providing explanations of decisions made by the AI technique. The Human Centric AI (HAI) explanations proposed in the work of [30] take the form of generated text-based explanations attached to the features within weighted paths in the neural net; with this approach, a most weighted path or feature combination may resolve into a text explanation. HAI has the aim of achieving human trust in AI in combination with the effect of further contextualization of the explanations provided by explainable AI approaches [30].

Hoffman *et al.* [31] examine the need for metrics for the assessment of an explainable AI system. The authors examine the current efforts to mirror human mental models within software systems and conclude that metrics (and measures) for XAI will differ by area examined.

Sheh and Monteath [32] propose the following three dimensions for the categorization of Human requirements of an XAI capable system: Source - this category considers the source of the explanation that will be offered by the system, e.g. is the source black box or a more open system; Depth - describes how attributes within a given system are used in the process of decision making, also how a model was generated (explanation of model generation); Scope - this is the scope of the explanation, dividing into 'justification' or 'teaching' which is an accompanying explanation of the justification given.

Xu *et al.* [22] note that black box operation algorithms such as those used for deep learning (neural networks) provide a particular challenge to interpretability by Humans, often leading to questions of trust being raised. Chen and Ran [33] go on to explore so called 'glass box' design models where human understandable explanations are provided by the system, stressing that the results produced by such systems should also be understandable in real-time processing cycles not just after the results have been collated and presented as an already actioned decision. The field of Human and machine teaming is explored by Adadi and Berrada [34] who point to the absence of Human friendly explanations as an interface for machine systems, these authors cite XAI approaches as holding the potential to address this need.

V. AUDIT TRAILS FOR MANUFACTURING

One particular avenue of investigation for the communication of automated system reasoning to humans, and in particular in relation to explainable AI utilization, is that of audit trail use. An audit trail can be thought of as a time stamped consecutive series of transaction recordings. As such, the audit trail can provide a construct for verification and assurance of provenance when considering temporal event based industrial data [35]. Swartout [36] propose a system that might be described as an ''audit trail'' of expert reasoning, where justification of programing code constructs of a given software are generated based on execution traces. Turner *et al.* [35] illustrate a potential way to use audit trails for the control of decision making within systems for predictive maintenance intervention. This work also promotes the ability to 'mine' information streams, captured in the form of raw recorded data logs, in order to derive the major stage gates in the decision-making process. Process mining as a practice has been used to identify primary processes from event log data generated by ERP (Enterprise Resource Planning) systems, initially for the purposes of conformance checking IEEE Task Force [37]–[39]. Though, such identified processes may also be used to outline the route taken by automated decision-making systems and so reveal the reasoning behind the decisions made.

Audit style organization and processing of data is also facilitated through distributed ledger technologies such blockchain (the technology underpinning the bitcoin currency [40]). Abeyratne and Monfared [41] put forward a study examining the use of blockchain in manufacturing and make the point that the use of this technology aids transparency in the monitoring of data in real time, increasing trust levels through its inherent authenticity. Samaniego *et al.* [42] recognize the use of blockchain with IoT (Internet of Things) sensing technologies as a method of ensuring the secure and ordered storage of streams and configuration data of physical assets. Lee *et al.* [43] put forward a framework for the consideration of blockchain use in the context of Industry 4.0 and CPS (Cyber Physical Systems) technology use, noting that distributed leger technology can encourage the further sharing and communication of data within and outside the organization. Andrews *et al.* [44] also make the point that traceability of parameters is possible through Blockchain and in terms of the supply chain the tracking of the '''use'' and ''effect'' ' individual data points.

Data related to both product-based and asset lifecycles can also provide a rich vein of information [45]. The increasing availability of intelligent assets and their ability to provide real time and near to real time views of their in-use behavior is a parameter set that readily lends itself to auditing. As with Andrews *et al.* [44] Angrish *et al.* [46] highlight the rise of product customization and the need to ensure the often decentralized and distributed nature of such customer centric information requires a structured and methodical framework for its communication and use; a movement that is likely to accelerate with the rise of the batch size of one/mass personalization [47]. Given such granularity of data analysis and profusion of its potential processing locations the complexity of the data management challenge becomes obvious along with the need for artificial intelligence and automated decision making. Understanding the context in which a decision making occurs is a vital strand linking both explainable AI and audit trail use. The field of context aware computing and its role to this end will examined in the next section.

VI. CONTEXT AWARE COMPUTING

The field of context aware computing involves an intelligent system gaining the capability to assess potential actions given additional information about a context or environment in which it operates [48]. Alegre *et al.* [48] make the point that many research works in this field concentrate on solving specific problem even though a more joined up and holistic approach is actually required to achieve real world context awareness in intelligent systems. Closely related in the concept of ambient intelligence which Gross [49] describes as embedded technology used improve users work and social interactions. Building on the pervasive physical infrastructure provided by ubiquitous computing, in the form of smartphones and sensorized devices and intelligent products, ambient intelligence provides the processing and presentation of data as knowledge to the user. Providing human centric context awareness to such a network of devices is seen as the next major development step for both ambient intelligence and ubiquitous computing paradigms [49]. Piccialli and Chianese [50] describe a move towards the 'intelligence age' where autonomous sensing will provide contextual inputs describing the immediate environment of the human user. These authors [50] point to IoT as the provider of the ubiquitous sensing capability and interconnectivity that may drive context awareness. Sezer *et al.* [51] also point to the rise of intelligent context aware data processing as the next step leading from IoT heterogeneity and standardization efforts. Gil *et al.* [52] Extend this use of IoT and outline Social IoT (or SIoT) whereby IoT devices acts as a combined social network.

In terms of establishing context from the sensed environment the research of Unger *et al.* [53] adapt recommender systems to working with data points provided in real time by environment-based sensors. In particular Unger *et al.* [53] detail the extraction of context utilizing mobile devices and find that challenges exit in data dimensionality and need to process data over time to extract meaningful context descriptions. The use of context aware computing in a manufacturing context is examined by Alexopoulos *et al.* [54]. In this work [54] put forward a system for the distribution of sensed context related information in an industrial environment. A case study involving a white goods manufacturer is used to illustrate the approach. The following functionalities are supported by this system in a context aware mode [54]: Material handling; Production planning & real time status; Shop Floor product assembly support; Shop floor notification. These authors also point to the value of context information in decision support at an enterprise level.

The need for next level intelligence to assist with or automate the decision-making process in some systems naturally leads to a consideration at some level of context the need for computational context awareness. Belkadi *et al.* [55] describe an intelligent assistant system with the aim of providing context aware support to engineers working on aerospace applications. In this work [55] provide a case study of an application that allows for workers to study the effects of their manipulation of aerospace parts. The approach of [55] required workers to record their expert knowledge and observations regarding discrete sections of aerospace related work in a knowledgebase system providing data entry tabs for the annotation and addition of: simulation model files; basic task knowledge; best practices; other ad hoc but related documents. While seen as a beneficial tool the system described by [55] does highlight the necessity for workers to impart their knowledge fully and correctly to avoid limitations in the context awareness of a partially populated knowledgebase.

Emmanoulidis *et al.* [56] identify different categories of contextual information relating to the management of industrial assets and make the case for the use of linked data; where context-based linkages between data and knowledge are resolved through the use of entity based semantic descriptions. In examining the case for the exploration of linked data an architecture for its collection and consideration, utilizing data management and machine learning approaches, is put forward by Emmanoulidis *et al.* [56]. Wider research is also progressing in the direction of semantics and ontology use to help develop improved context awareness in computational systems. Hoffmann *et al.* [57] illustrate the potential and applications for embedded context aware monitoring and control devices. In this work the authors [57] conclude that one of the major barriers to the further development of context based system is the need for explainable outcomes from automated decisions noting that 'correlation alone does not necessarily imply causation'; these authors also note the ongoing need for a 'human in the loop' to adjudicate where constraints in a learning based system provide no satisfactory decision in terms of the processes that may be automatically enacted [57].

VII. VISUALIZATION AND INTERACTION

The role of visualization is key in the operation of any human mediated system. As the possible interactions and data sets for consideration as learning materials for automated systems increases at an exponential level the value of clear communication media is paramount. Li *et al.* [58] provide a categorization of visualization methods for use with Human Computer Interaction (HCI) designs. In this study [58] a process for the selection of an appropriate HCI design method is outlined. Tran and Li [59] explore the human vision system in order to derive better visualizations that are more appropriate for the understanding of complex data sets and streams. Acknowledging the limitations of human vision and perception the authors propose a set of multidimensional graph types more suited to increased ease of perception by the human subject.

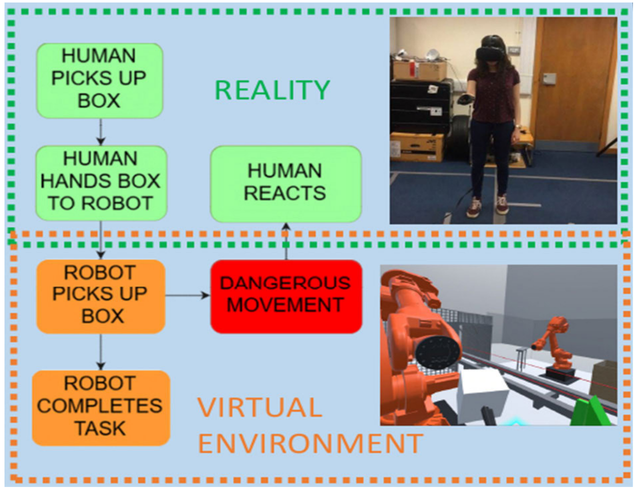

FIGURE 3. Using a digital twin to study human-robot collaborations [65].

In terms of visualization for manufacturing applications Zhou *et al.* [60] highlight the importance of the role of visualization in an Industry 4.0 and Smart systems enabled environment; acknowledging the need for human legible communication across automation, product design and development and production scenarios. In terms of the content most likely to be depicted visually Lade *et al.* [61] provide five categories of analytics seen as key to productivity improvements in manufacturing: Reducing test time and calibration; Improving quality, Reducing warranty cost; Improving yield (benchmarking lines and plants); Predictive maintenance. Golfarelli *et al.* [62] propose a method to automate the graphical presentation of analytics source data sets, where particular graph types are matched to best resolve patterns in the data.

The Digital Twin concept promises to provide real time connectivity with and control of manufacturing systems [63]. Digital Twin has been defined as the linking of a physical entity with a digital representation for the entirety of the physical entity's lifespan [64]. Visualization, often multi-mode in nature, is key to the implementation of this concept. These visualizations offer a user a close to real life representation of the application domain (Fig. 3) which could then be used for the training of workers (Fig. 4).

The inherent real time representative nature of Digital Twin is different to a simulation, which focuses more on offline what-if experimentation [26]; though simulation technology may play a role within the overall concept. Turner *et al.* [66] make the point that the use of Augmented Reality technologies may allow for the real time overlay of Discrete Event Simulation model layouts over live production line scenes, via headsets and handheld devices, allowing for round trip decision making to be facilitated though such Mixed Reality environments. Hutabarat *et al.* [67] make the case that Virtual Reality renderings of manufacturing scenarios may be enhanced through the use of motion and depth sensing technologies such as Kinect. In [67] industrial shop floor layouts are considered and models built that allow for user manipulation of Discrete Event Simulations via workers' voice commands and movements in real time. The use of RFID (Radio-Frequency IDentification) tags to track and control logistics processes on the shop floor has been explored by [68]; with a particular focus on the visualization of logistics trajectories the paper proposes a logistics object based on RFID cuboid data structure, enabling simplified views of raw sensor derived data.

Negri *et al.* [69] and Cimino *et al.* [70] highlight the role that Cyber Physical Systems are likely to play in the future of manufacturing and discuss their management and control via Digital Twin visualizations. In these works, the need for more research on control loops between Manufacturing Execution Systems and shop floor production via Digital Twin is highlighted. Digital twin has also been explored as a way of controlling and visualizing information flows for holistic product development, where the performance of developed products in the field can be fed back into new designs at the CAD (Computer Aided Design) stage [71], [72]. Often seen as the preserve of large corporations [73] make the point that SMEs (Small and Medium Size organizations) can also benefit from the Digital Twin; in providing an approach for unified data acquisition from production systems this paper provides the potential for the emergence of a lower price point solution of relevance to a wider range of companies. Lu *et al.* [26] go onto highlight a number of areas open for additional research relating to Digital Twin and visualization as: How much should autonomous operation of and feedback from manufacturing systems be facilitated through Digital Twins; Need for improved integration of humans with Digital Twin technologies.

Certain innovations in the graphical display of data particularly lend themselves to the visualization and snapshot analysis of streaming sensor data. Vosough *et al.* [74] introduce a refinement to the display of ribbon flow diagrams involving the communication of uncertainty; the work involves the utilization of a case study based on data sets relating to an industrial pump product, mixing both technical parameters with market data in the same graph. Qin *et al.* [75] explore the possibility to automate the process of matching data with appropriate diagrammatic visualization types. Luo *et al.* [76] go on to further develop this approach, achieving a system that make a rage of visualization recommendations when presented with data; utilizing a learning technique that makes use of existing examples, users can also enter keywords to further influence the systems choice of visualization. With the aim of further exploring the automated generation of graphs from data the field of Graph Grammars may lend itself to such context-based display of industrial data. Zou *et al.* [77] provide a commentary on Graph Grammars in relation to the comprehension of complex systems within visual programing languages; in this work the focus on the establishment of context is realized, this is examined in relation to the successful combination of disparate parameter sets. Lensen *et al.* [78] approach the generation of graphs from data with the aim of providing a reasoning for how such visualizations are generated. In this work Genetic programming is used to 'evolve interpretable mappings from the data set to high quality visualizations' [78]. Finally Silva *et al.* [79] highlight the role of ontologies in relation to visual data analytics. Proposing an approach capable of eliciting undiscovered relationships between data.

TABLE 3. Some state-of-the-art in using cobot for idustry tasks.

Industry scenario	Tasks	Advantages
BMW [83]	Fitting insulation inside automotive door	Replace human worker
Audi [84]	UR3 Cobot (Collaborative Robot) for adhesive on automotive product roof	Save space
Volkswagen [85]	KUKA Cobot for attaching automotive drive train	Operate in difficult to reach locations
ARM [86]	Material prepreg for composite lay up	Reduce human operator workload

VIII. COLLABORATIVE ROBOTICS

The main advantages for human-robot collaborative systems specifically in manufacturing system is that robots can assist human operators. In this manner, the machines do not replace humans, but they supplement their ability to perform tasks. Unlike traditional industrial robotics, collaborative robots (also known as Cobots) in manufacturing systems can offer a higher degree of safety and flexibility [80], [65], [81]. Such Robots can combine the precision and speed of machines with the dexterity of human hands [82]. A robot can also learn from human and programmatic demonstration [82]. In order to adapt to market demand, manual assembly systems can be used, although this may lead to a decline in productivity due to changes in quality and fluctuating labor rates. By comparing the capability of the manual operator with that of the automated system, it can be seen that the performance of manual assembly is greatly affected by ergonomic factors, with limiting factors being the part weight and precision of the of the manual operator. Thus, these limitations reduce the ability of human operators to maneuver and select heavy/large parts.

Traditional robotic systems fill this gap, assigning robots to heavy load handling tasks (e.g. FANUC m-2000 series, 2.3t) with repetitive cycles. However, the flexibility and agility required for complex assembly tasks may be too expensive to achieve even with traditional robotic systems [82]. This gap can be closed through collaborative systems as they combine the capabilities of traditional robots with the flexibility and agility of human operators. Collaborative robots are particularly advantageous in assembly tasks, especially when the task is performed by a human operator. They can also be used to pick and place items, although using traditional robots or processing systems can provide better results in terms of speed, accuracy, and load. Some examples of the industrial use of collaborative robots in manufacturing systems are presented in Table 3.

In order to better understand human and infer human intention, a collaborative robot should have the perception to collect raw input data to the internal system representation for cognitive tasks [87], [65]. There are three main sensory modalities used in research including vision, impendence control, and audition. Robot vision is a feature developed in the 1980s and 1990s. Engineers have developed various intelligent software programs that provide robots with the capability to ''see'' their environment. This often comprises of a camera mounted on the robot or in a static position to take pictures of each artifact the robot will interact with. If this part does not match the algorithm, it will be rejected – the robot will not interact with it. Vision can also be used in non-robotic ways. For example, a camera can be placed on the conveyor belt to take pictures and compare them with the loaded algorithm to accept or reject the product's quality control. If accepted, send in one direction, if rejected, send in the other. Vision could also be used to collect data from legacy machines using techniques described in [67]. The quality of visual processing has improved considerably with the popularity of software/hardware toolkits. Vision can also be used in a digital assistive system that digitizes manufacturing tasks in real time and provide feedback to workers [88]. Teke *et. al.* [89] adopts Kinect V2 sensor's RGB-D image on a Universal robot based utilizing Euclidean distance to improve the efficiency of interaction. Fang *et.al.* [90] adopts Cloud Point Library to segment the depth image for object localization. Song *et al.* [91] utilized RealSense SR300 RGB-D camera and depth image for 3D vision object grasp. In human-robot interaction, the impedance control is used to measure the force where the manipulator interacts with the operator and infer the relationship between the force and position. Rozo *et. al.* [92] implemented stiffness estimation via force sensors to measure the interaction model from demonstration. Townsend *et.al.* [93] measures the force and velocity between two operators co-manipulation to estimate the intention of the humans [80]. Audition is another common modality as sounds or voice can be used to guide an intelligent system or communicate with it. Zhu et. al [94] proposed a methodology to combine speech recognition and haptic control to teach the robot by demonstration utilizing a universal robot in the completion of automotive assembly tasks [65].

IX. INTERNET OF THINGS INTELLIGENCE AT THE EDGE

Edge computing is a relatively recent innovation involving the use of miniaturized low power consumption computer processing devices utilized for the intelligent filtering of streaming data for local decision making, with such data often produced by discrete or machine-based sensors. It has been seen in section III that sensor outputs from intelligent products can form a valid part of an auditing process, especially in order to understand the in-situ Edge mediated decision making that may occur in the operation of such assets. The role of Edge technology in IoT applications has been a relatively early application of this computing approach with [95] proposing an architecture designed to utilize the power of localized processing in combination with computationally intensive Artificial Intelligence (AI) algorithms. In [95] Cloud resources host the machine learning algorithms with local processing of streaming sensor data.

The need to perform data analytics at the Edge is outlined by [96] who also identify the need for localized deployment of intelligent techniques for initial data processing with more involved machine learning based work performed in the cloud. Chen *et al.* [97] and Sun *et al.* [98] acknowledge the value of Edge in the delivery of manufacturing and industrial solutions to the need for localized processing of data streams, with the assistance of machine learning techniques [99] including Deep Learning [100], [33]. Novel contributions utilizing Edge can also be found in [101] who examine the connection of production line Robots relying on localized processing and [102] in relation to Edge based context aware monitoring of workers via wearable sensors. A concern, partially addressed by Edge computing's ability to preprocess and filter voluminous data streams before forwarding to requesters, is that of network bandwidth (especially considering the need for the use of wireless transmission). Cheng *et al.* [103] provide an overview of the potential for 5G mobile communication technologies to enable high rates of data transmission with increased reliability and heterogenous acceptance of diverse machine and sensor types with (eventual) plug and play ease; this work has particular relevance to Industrial IoT (IIoT) applications. The application of 5G would support the possibility of having ''connected'' workers that are able to acquire more granular data regarding the manufacturing system efficiency and performance as well as receive up to date machine intelligence processed information and knowledge to decide the next steps. This scenario would make for a more ''hive-like'' interconnected heterogeneous entity (man, machine, machine intelligence hub).

X. NEXT GENERATION MANUFACTURING MANAGEMENT

Swarm engineering [104] has the aim goal of enabling a collection of robots to collaboratively solve the real-world challenges in manufacturing. The robots in such a collective are called swarm robots. Swarm robots are low cost agents that run simple computational cheap algorithms. By deploying them in large numbers, they have the capability to complete tasks that a large and expensive robot will struggle

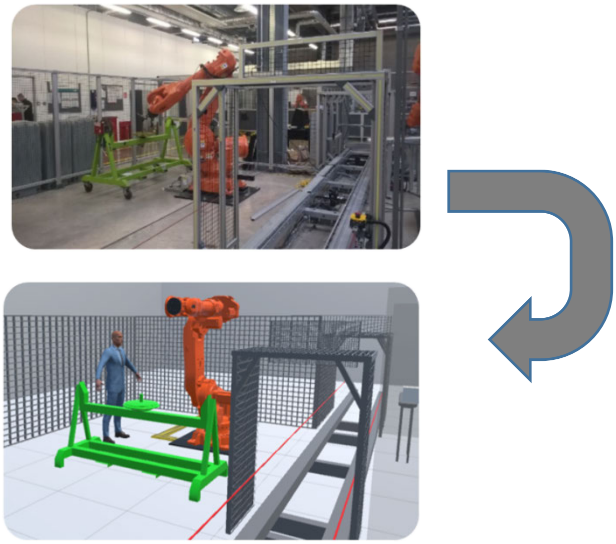

FIGURE 4. A digital representation of a physical space [65]: (i) A real world workshop; (ii) Workshop environment replicated in unity.

to perform on its own. Although swarm robots have been successfully applied for surveillance [104], mapping spatio-temporal quantities [105], [106], the applications in industry mainly comprise of manipulation [92], [93], transportation [106], [108], and assembly tasks [109], [107]. Nevertheless, in swarm engineering there are still a number of open research challenges including: (1) how to develop human-multi-swarm collaboration strategies in such a way that the human is not overloaded cognitively; (2) how to engineer and reconfigure swarms to new tasks with very little effort (3) and how to optimize the swarm behavior. These research challenges become even more sophisticated and interesting when heterogeneous cyber-physical swarms are considered. It is possible that a multi-disciplinary approach including manufacturing, psychology, engineering, embedded AI and complexity science could offer relevant tools to address the aforementioned scenarios. Combining the efforts of researchers in these fields could result in new trans-disciplinary theoretical frameworks that integrate and move beyond the current state of the art. Nevertheless, human intervention in a supervisory role might still be needed in ensuring that the swarm system is still operating according to goals and within the confines specified. Also, humans would still be needed to ensure that damaged swarm individuals are repaired timely for redeployment.

XI. SCENARIOS FOR NEXT GENERATION PRODUCTION SYSTEMS

Fig. 5 illustrates five scenarios utilizing the digital manufacturing technologies detailed in this paper. The scenarios range from simple automation with data mining of event logs to the integration of sensed data streams and the context-based audit trail description of machine learning decision making systems to the realization of fully automated production with human in the loop oversight. In next generation production systems as described in scenario 5 (shown in Fig. 5), humans would benefit from intelligent manufacturing technology to perform more supervisory level activities required by lights-out type factory scenarios, either at a local site or remotely. This would raise many challenges in the sense that new paradigms of controlling a fleet of robots would need to be developed. An example of such a paradigm could be swarm robotics. This would give the human an opportunity to provide a high-level command which could then be broken down into individual level actions. This would necessitate a paradigm in which the human is kept in an automation loop that involves multiple autonomous agents feeding ''knowledge'' to the human to assist high level decision making. To date, industrial robots have been successfully deployed in manufacturing in a variety of forms. Moreover, as the manufacturing environment is dynamic and uncertain, it cannot be expected that one single robot can fulfil all the given tasks. Therefore, to enhance the efficiency and robustness of the system, the concept of swarm robotics, which is inspired by the collective behaviors of social insects, can be introduced.

XII. RESEARCH GAPS IN ACHIEVING THE SCENARIOS FOR NEXT GENERATION PRODUCTION SYSTEMS

The scenarios outlined in section XI are challenging in their scope and provide a research agenda in their use of new technology. Table 4 details a range of technologies utilized in the scenarios and summarizes the main reasons these approaches are required, highlighting the areas still requiring further research. From Table 4 it can be seen that Explainable AI (XAI) techniques are envisaged to play a central role in the delivery of narrative reasonings to supervisors of automated production line systems. The enhancement and incorporation of human reasoning to be used in concert with automated systems is receiving greater attention. Romero *et al.* [110] provide a new direction in putting forward the Operator 4.0 paradigm, where humans are empowered by Cyber Physical Systems (CPS) rather than replaced. In the engagement of human operators, it is important to contextualize the responses from automated systems providing additional detail and relevance for the recipient. This may in part be achieved through the use of metadata tagging for collected data streams and semantic processing to establish and present context relevant reasoning. Work in a similar direction includes [111] where workers are equipped with wireless sensing tools and devices with the intention to improve the safety of workers in industrial settings through monitoring of human vital signs and interactions with machines they operate.

It is the case, from the findings of this research, that future work must be directed towards the further development and use of XAI along with semantic mining of sensor streams to provide stage gate style decision reasoning to production line workers. In addition, further attention needs to be given to the visual presentation of such information in a context relevant manner. To this end the use of Mixed Reality technologies, in particular Augmented Reality (AR) graphical overlays

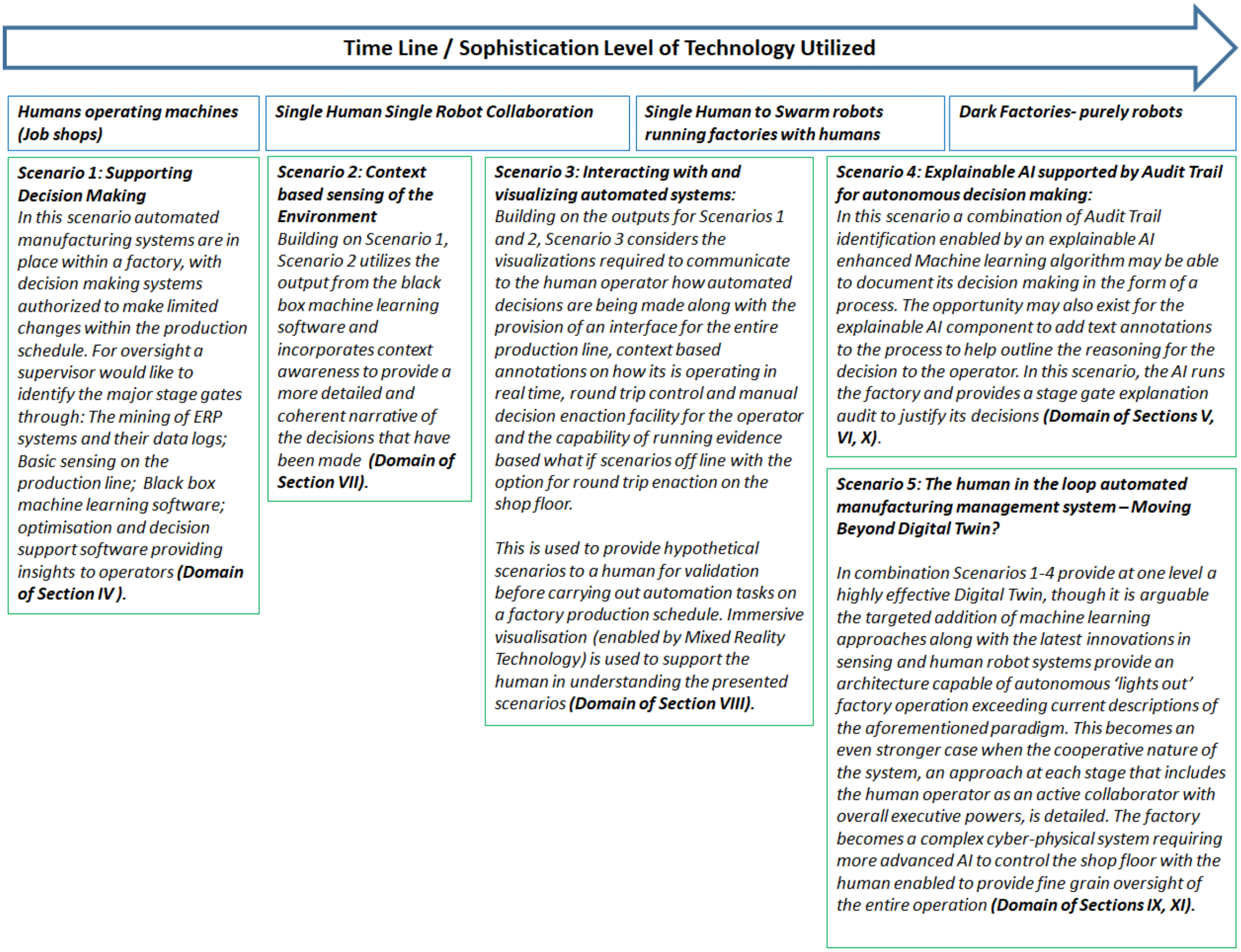

FIGURE 5. Scenarios for human mediated technology adoption in manufacturing practice.

(presented though line of workers sight via. headsets), and even outline simulation models need to be developed to communicated automated decisions and their potential effects (in the locality of the production line itself) [66].

The use of the Audit Trail concept in data mining is well known, especially in the area of business process mining [39]. The potential exists for the use of Audit Trail in the mining of data produced by production line machines and manufacturing control systems such as SCADA. Audit trail use in the recording and organization of manufacturing sensor stream data is currently limited, more research is required to investigate the types of data and sources that are best suited as contributors to the realization of structured event or activity capture and description. In addition, the application of machine learning to this area to identify the potential major stage gate decision points within semi-automated production systems is required in order to identify such trends in fully automated production scenarios.

The use of XAI to relate automated decision to humans in the form of a stage gate audit trail is the eventual 'control' accompaniment to future highly automated or even autonomous systems. Such systems will, in the opinion of the authors of this paper, still require human oversight and in some cases intervention. Easily communicable event status data needs to be presented to humans in a form that facilitates drill down and reasoning so that problems and deviations from normal operation can be rectified with the minimum of delay and disruption to production runs.

The research area of human to machine interaction is also relevant due to the need for human inputs to be interpretable by production line automation and robots. The use of machine learning as an enabler for human to machine communication requires additional research and the scenarios in this paper provide an agenda for that work.

In the application of swarm to manufacturing, reinforcement learning or swarm evolutionary machine learning paradigms will need to be further developed. This is necessary to develop reconfigurable and general-purpose swarms that adapt to the goals of the manufacturing enterprise such

TABLE 4. Research gaps in achieving the scenarios for next generation production systems.

Technology Approach	Why Needed	Research Gap	Scenario
Explainable AI (XAI) approaches applied to manufacturing production line control focusing on provision of major stage gates in automated decision making/support process	To provide trust and understand reasoning in the actions of automated systems Explainable AI (XAI) approaches are required for the human supervision of production line control automation	Use of XAI Approaches to allow Black Box Machine Learning systems to communicate stage gate decision reasoning to manufacturing workers	Scenarios 1 - 5
Context based reasoning with, and automated metadata tagging of, production line sensor streams.	Can provide an additional text-based reasoning for automated decision making based on the intelligent processing of metadata tagged sensor streams, supporting the stage gate decision making and addition further detail for the human user.	Further research is required into the development of semantic and contextual sensor stream tagging in concert with XAI techniques to provide meaningful text explanations of automated decisions by production line systems.	Scenarios 2-5
New visualization approaches utilizing Mixed Reality Technology to aid interoperation between workers and the digitized production line	Complex data streams and automated decision-making outcomes would be produced at a rate that would be difficult for a human to interpret in real time. The combination of a Mixed Reality environment (via headsets) combined with carefully chosen graphic representations would help to summarize and contextualize the information presented to the production line worker.	The area of exploitation of contextualized real time data streams in combination with XAI technology is currently lacking in examples. The presentation of such data with Mixed Reality headsets in a manufacturing environment is an additional future research target.	Scenarios 3-5
Mining of Audit Trail logs to improve understanding of production line operation and use	The systematic sensing and capture of production line events is required in order to assemble a real time picture of manufacturing. The Audit Trail abstraction provides an ordered way of organizing a time stamped record of the operation, which may then provide structure to both XAI approaches and context based meta-tagging. This enables the provision of an enhanced stage gate reasoning of automated decision making, comprehensible by humans.	Audit trail use in the recording and organization of manufacturing sensor stream data is currently limited and requires more investigation. Audit trail and metadata tagging for use with XAI technologies is also another area for further exploration.	Scenarios 4-5
Collaborative Robot (Cobot) development	The advantage of having human teams in manufacturing systems that make use of shop floor is that such a manufacturing system can be rapidly reconfigured to product changes and variations by rapidly trainings staff to assembly new products. This becomes a challenge when the product order outstrips the current numbers of experienced staff members. Cobots offer a way to temporary fill this gap.	Current Cobots are kinesthetically trained and this enables them to be rapidly reconfigured to a new task. However, such robots lack the ability to deal with variations in the workpieces and in the human they are collaborating with. Furthermore, their speed is reduced to a level in which their productivity is capped. This is to ensure that they do not injure humans. A way of removing such restrictions will benefit the deployment of Cobots on shop floors [65].	Scenario 5
Robot Swarm development	The ability to synchronize a large quantity of heterogeneous agents autonomously will greatly improve a manufacturing system's robustness to variabilities and disruptions. This ensures that organization can become resilient to changes and rapidly adapt. This would need to be supported by secured data feeds that ensure that such manufacturing system as the latest information to exploit.	A research gap exists in the use of multi-agent swarm and evolutionary learning paradigms to explore and find strategies that enable swarms to the rapidly reconfigured and redeployed to new tasks as required by the manufacturing system. This would be a challenge for XAI because it introduces more layers of complexity that the XAI system would need to extract and explain to a human.	Scenario 5

as shifting the swarm goal from transportation of discrete materials to using them to perform rapid inspection of large-scale artefacts and structures such as airplane wings. The challenge here will be to develop algorithms such that control rules can be rapidly found and deploy. Algorithms such as reinforcement learning, especially multi-agent reinforcement learning, require a significant amount of computation time to find the right policies that are useful for the task at hand. This is a challenge that needs to be overcome. Ensuring even energy utilization across the swarm members is another challenge that needs to be solved in order to ensure that the swarm as a whole completes the task [112].

According to conclusions in [113], several challenges of multi-agent reinforcement learning also include:

- The curse of dimensionality: The dimension of action or observation space will grow exponentially with increasing number of agents

- Difficult reward shaping and assignment: correlated reward of agents cannot be optimized independently as the number of task scenarios and the noise of returns are increased.
- The non-stationary environment: the individual learning of an optimal policy is influenced as other agents act. This is also supported by [114] in which they suggested that observation of policies of other agents would stabilize training of MARL
- Exploration-exploitation problem: multiple agents learning simultaneously can bring much exploration resulting in instability.

In more recent work Nguyen *et al.* [115] details progress made in the combined use of deep learning approaches with multi-agent reinforcement learning. In Nguyen *et al.* [115] the addition of deep learning can help to address the dimensionality problems encountered in earlier approaches though challenges still remain in its application to more complex areas outside the realm of relatively simple resource allocation and planning and optimization systems. In [116] they designed critics for each agent. Each agent had access to global states of the system in a multi-agent actor-critic framework. However, these frameworks may not fit the swarm system due to the large number of critic neural networks. Thus, inspired by distributed optimization, a scalable centralized multi-agent policy gradient algorithm is suggested in [117] where they only update one centralized policy by taking the projection on the individual policies. Oroojlooy and Hajinezhad [118] make the case for future research in the direction of optimization algorithm use with multi agent deep reinforcement algorithms; and in the implementation of both deep learning and optimization algorithm theory to provide new levels of applicability to more complex problem spaces, such as that posed by nonconvex and non-smooth optimization challenges posed by manufacturing automation and robot/human collaborations. Papoudakis *et al.* [119] provide additional commentary on the use of independent learning, value decomposition and centralized training with multi agent deep reinforcement algorithms.

The above considerations become even more complex when humans are introduced into the loop. This is because of the variability that humans use to perform tasks. Even the same tasks are performed differently by different humans [120]. This is because when introduced to a new task, humans tend to explore various strategies to ensure that the task is performed optimally while using as little energy as possible. Once a strategy is found, it is used repeatedly. When given similar task families in the future, the human makes use of the past strategies learnt is similar tasks and apply them. As a result, robots should be given the capability to understand the human intentions, goals as well as their preferred way of completing a task. This involves research into the psychology principle of theory of mind [121].

So far, reinforcement learning which has its roots in Psychology has been applied by numerous researchers in robotics. Reinforcement Learning (RL) approach offers another possible solution for Human Robot Collaboration. Instead of trying to understand human performance, Reinforcement Learning treats them as a system of states [122]. The quest to find an optimal policy, multiple optimization algorithms could be used. However, as the variations in the environment increases so does the number of states to explore and this also leads to a combinatorial explosion. It will be advantageous to find alternative optimization algorithms or a transfer learning mechanism by which robots do not have to start learning from scratch for various tasks. Until these are found, it is most likely that for the foreseeable future, human directed kinesthetic training of robots will continue to be utilized. This answers the first research question posed:

RQ1: Why might the human still have a role? In other words, it is expected that human interventions, especially as the variation needed in the manufacturing system grows with an increased volume of bespoke goods, will still be required. Humans offer levels of flexibility and decision-making capabilities that are still beyond the current generation of AI applications and robotics; this situation ensures that the need for humans to intervene in automated scenarios will still exist in both medium and long-term future scenarios.

RQ2 Are there limits to 'lights out' manufacturing? It seems that with the current state of manufacturing systems paradigm, there will be a limit based on the type of product being manufactured. If it is possible to know beforehand what types of product variants are going to be manufactured, then it is possible that a factory can be operated in lights out mode without the need for human interventions except when break down occurs. However, as the various regions of the world become more connected with changes in trends spreading overnight across geographical boundaries, it is the companies with the ability to quickly adapt their manufacturing systems to these changing trends that will remain competitive. Since humans have the ability to quickly adapt, they will be needed in such scenarios. As a result, this is a limit to the concept of 'lights out' manufacturing.

RQ3: Is the 'Human in the loop' concept required? The 'Human in the loop' concept is not just necessary, but a desirable end goal for research activities involving automated manufacturing.

As a result, of the above, the 'human in the loop' concept will still be necessary for some time to come and we propose that this should be a desirable end goal for research activities involving automated manufacturing. In fact, it is interesting to note in [123] that, in the latest research agenda of the European Union, that so termed Human Centric technology are now central to the delivery of next generation manufacturing systems of a conceptual Industry 5.0 paradigm. These; systems that aim to empower Human workers, enriching their job roles while improving productivity levels within an environmentally sustainable and resilient manufacturing ecosystem. It is the ethos of [123] that human needs and interests should be the central motivation behind the new production processes of the future so that workers' rights within manufacturing should not be degraded but respected.

XIII. CONCLUSION

This paper has identified a need in existing research works to justify for the present and future need for 'humans in the loop' and the effective role that they may play. In addressing this gap, the research questions posed in section I and discussed in section XII, along with the outlined scenarios, provide a more focused agenda for the further development of human centric automated manufacturing in the future.

It is clear that for more complex automation projects involving manufacturing systems engaged in mass production of highly customized or personalized products the human decision maker is still going to be a key component. Even autonomous production scenarios, employing advanced machine learning techniques, still benefit from the human operator as an active collaborator with overall executive powers. Realized in Scenario 5 (shown in Fig. 5) the factory is a complex cyber-physical system requiring more advanced AI to control the shop floor with the human enabled to provide fine grain oversight of the entire operation.

This paper has set out a research agenda to address remaining gaps in approaches that aim to realize human centric next generation manufacturing systems; with a particular focus on the role that Explainable Artificial Intelligence (XAI) technologies may play along with Collaborative Robots (Cobots), summarizing the work still required and ongoing to optimize such systems to a level acceptable to all human workers engaged in manufacturing industry.

While many manufacturers will seek to employ some of the technologies described in this paper, utilizing scenarios not too dissimilar to those described here, it is key that for the foreseeable future, humans have oversight of the information flows and remain an active participant in the delivery of the next generation of production systems.

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