Smart Collaborative Systems for Enabling Flexible and Ergonomic Work Practices

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Introduction

The manufacturing industry is among the top wealth-generating sectors of the global economy, which accounted for 15.3% and 10% of the total European and American workforce in 2018, respectively [1], [2]. Despite its crucial role, it is facing a critical challenge based on a reduction of skilled labour availability. This trend is imposing a bottleneck on growth due to the demands of an increasingly competitive market. The ageing workforce is not helping this shortfall either, as the available workforce is less able to perform burdensome industrial tasks in an efficient and productive manner.

Efforts are being made to respond to such challenges in the manufacturing scenarios, and to promote higher quality and more efficient operations. Manufacturing automation by means of robots is widely known as a promising approach to combat such human-centric issues that have been brought about by inherited layouts and processes. Such automation efforts attempt to make complex operations easier for employees to comprehend and support the completion of physically demanding tasks. However, today's solutions require huge initial investments and are often bespoke for particular scenarios; hence they are not flexible enough to cover all of the requirements of a dynamic, high-mix production environment, typical for small and medium enterprises (SMEs). These solutions also demand, and to a certain extent dictate, very specific layouts and work-cell formats that are 'robot friendly' [3].

Towards a unified perspective of boosting the competitiveness of the European manufacturing industry, in 2012, the European Commission set the goal of raising manufacturing's share of gross domestic product (GDP) in Europe from 15 % to 20 % by 2020 [4]. In this direction, more companies have been encouraged to realize the potential of Industry 4.0, to achieve higher levels of automation, autonomous processes and machinery, and data exchange in manufacturing domains, to respond to the customisation needs of the future. Customised products are best produced close to the market, to quickly respond to customer needs and to reduce delivery times. This change implies challenges to the way work and resources are organised within a factory to guarantee cost-effective productivity and quality and to reduce waste. In this vision, Human-Robot Collaboration (HRC) frameworks have a high potential, since they combine human beings' creativity and craftsmanship with the precision, repetition speed, and consistency of robots to perform complex skill-demanding tasks while improving work ergonomics. In addition, they can be redeployed to other tasks much more easily. The quality of industrial production is improved, the yield of smaller lot sizes is increased and the working conditions for humans are improved [5]. In fact, HRC has been a crucial enabler of the current industrial revolution, and will be at the core of the upcoming fifth industrial revolution [6].

To create HRC systems that can radically increase the flexibility and productivity of manufacturing while improving the ergonomics of the workplace, four fundamental aspects, i.e., technology, flexibility, interaction quality and standardization, must be covered comprehensively (see Figure 1). This has been the aim of the first wave of projects on development cobots itself (e.g., in Europe, AMARSI, SAPHARI, PHRIENDS), and subsequently, on development of their control and high-level interfaces (e.g., in Europe, SOPHIA), whose motto is "human-centred and modular design". Two distinct objectives of the new wave is to improve competitiveness [3], and to reduce work-related musculoskeletal disorders, which represent the single largest category of industrial diseases in first-world counties [7].

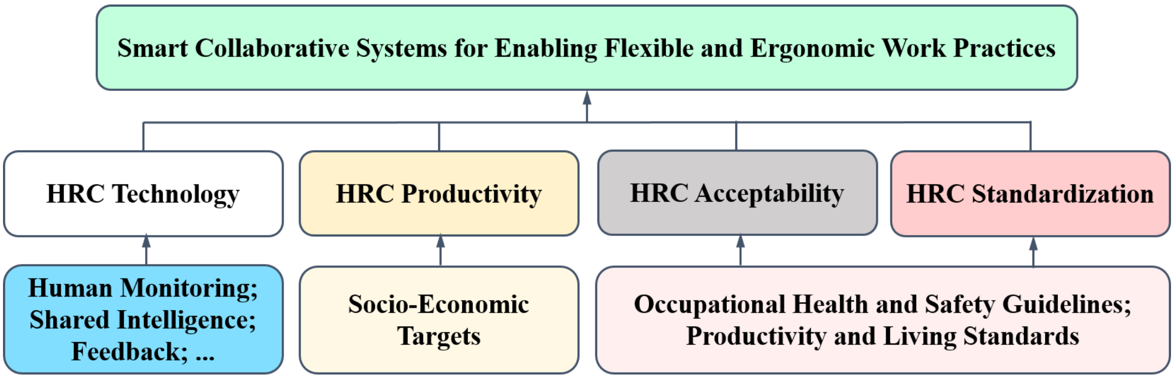

Figure 1. Several fundamental aspects, in addition to the technology advancement, must be taken into account to create flexible, productive, and ergonomic HRC systems.

HRC technology

Several technologies must be in place to enable humans and robots to work together to achieve shared goals. In this section, we place our focus on human monitoring, sensing and feedback interfaces, and shared intelligence aspects of the HRC technology, which have been less discussed in HRC literature, in comparison to the traditional safety and control aspects of the collaborative robots.

Human Kinodynamic Monitoring

The traditional solutions for ergonomic monitoring of industrial workers are mostly based on heuristic algorithms (e.g. using the ergonomics assessment worksheet (EAWS)) and do not have the required resolution for determining the function of individual muscles. This ultimately limits the design of effective technologies personalized to individual workers. Common monitoring techniques rely on simple measurements (e.g. limb accelerometry or kinematics) where the worker's ergonomics is determined based on whole-body postures. However, even kinematically correct postures may underlie negative muscle compensatory strategy that could increase mechanical tensions and loads on musculoskeletal tissues. Although complex and advanced biomechanical analyses exist, these are bounded to laboratory settings and are not viably transferable to factory settings because they often involve lengthy data acquisition and time-consuming offline analyses with quantitative results being generated only weeks after the initial subject's assessment. In factory settings, the accurate assessment of worker's musculoskeletal function should be performed via non-invasive sensing technologies that require short preparation time as well as advanced yet rapid musculoskeletal function-probing techniques that can provide instant data on the human musculoskeletal mechanics [8]–[10].

Computational musculoskeletal models can provide advanced analysis and understanding of body function during complex dynamic tasks [11]. Inverse dynamics models have been proposed in which the contribution of individual muscles to joint actuation is resolved according to *a priori* defined optimization criteria, (e.g. minimize squared muscle activation sum or metabolic cost of transport) and/or by enforcing pre-selected muscle reflexive rules [12]. However, current approaches are dissociated from *in vivo* body function and therefore limited in describing workers' body function in real-world scenarios. That is, it is not possible to know *a priori* what the human body really optimizes during a working task, if anything at all. Moreover, even though one model can be tuned to reproduce experimental data (e.g. electromyography (EMG)) in one instance, synergies between muscles, or even between motor units, are highly variable across tasks, training, fatigue levels [13] and directly influenced by the environment, e.g. assistive devices or working settings. Therefore, an alternative solution is needed that can capture workers' true muscle activation patterns and convert them into realistic estimates of musculoskeletal forces. A way to do this is by developing a new class of data-driven musculoskeletal models. The idea is to combine multi-modal body movement sensing with forward dynamics musculoskeletal modelling, i.e. as opposed to state of the art inverse dynamics based modelling techniques [14]. Data-driven modelling has been recently proposed for fusing 3D body kinematics and muscle electromyography (EMG) recordings and for simulating how muscles activate, how they contract and generate mechanical force about multiple skeletal degrees of freedom simultaneously both in upper and lower extremities without making any assumptions on muscle recruitment strategies [15]. More recently, these techniques were employed to connect robotic exoskeletons and bionic arms with the human neuromuscular system, thereby restoring lost motor function in neurologically impaired individuals as well as amputee subjects. Results showed that patients could achieve voluntary control of wearable robots and that the performance of the established human-machine interface did not deteriorate across large time scales, i.e. days and weeks [16].

Sensing and Feedback Interfaces

To enable an effective interaction between humans and robots, it is fundamental to ensure a correct information exchange between the natural and the artificial side. This requires suitable interfaces to monitor human behaviour - to properly plan the execution of the collaborative task - and strategies to increase the mutual awareness of the human-robot dyad. In literature, different solutions have been proposed to sense human behaviour in free motion or during the interaction with the environment. Regarding kinematic sensing, both vision-based and wearable devices have been developed with special attention to the hand (e.g. glove-based system or inertial measurement unit-based solutions, see [17], [18], and Figure 2). Recently, commercial and research solutions for whole body kinematic tracking have been introduced, see e.g. Xsense (https://www.xsens.com), as well as for accurate and wearable EMG acquisition e.g. Trigno by Delsys Inc, or FreeEMG by BTS Spa and ground reaction forces (http://www.moticon.de). In parallel, the usage of inertial units and low-cost wearable EMG devices (see e.g. Myo Gesture Control Armband (https://www.myo.com/)) has been successfully applied to implement body-machine interfaces for the control of and interaction with robotic and assistive systems (see e.g. [19]). For what concerns warning feedback to deliver to humans information on collaborative robot status, wearable devices usually rely on vibrotactile stimuli, which are also applied for guidance and human-robot-team cooperation [20]. Wearable haptic systems can be also an effective and unobtrusive solution to reproduce a wider range of haptic cues, since they can be comfortably worn at different body locations and stimulate locally the skin, by conveying to it different types of touch stimulations (see [21]). Regarding vision, in recent years augmented reality (AR) has gained increasing attention, and different commercial systems are now available for AR and for virtual reality (VR), e.g. Oculus Rift, Microsoft Hololens, Google Tango. In AR, components of the digital world may be superimposed upon or composed with the real world and used in teleoperation [22]. The composite scene can be displayed to the user, e.g. through HMD, to improve situational awareness in human-robot collaboration scenarios.

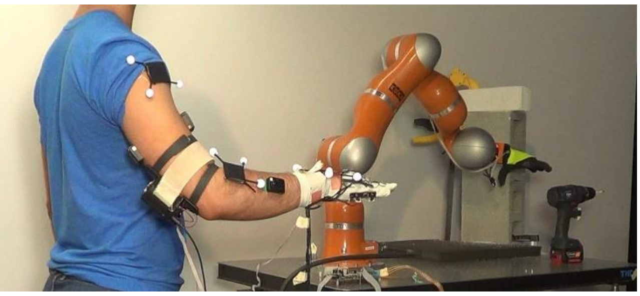

Figure 2. Wearable and lightweight sensing and feedback mechanisms can improve the usability and performance of the HRC systems.

Shared Intelligence

Task allocation schemes are developed to share the work between human and robot, depending on different factors such as capabilities, execution time, performance etc. A hierarchical framework for task allocation was developed that assigns a full sequence of atomic tasks based on the capabilities of each agent [23]. Similarly, in [24] complex tasks are split into basic subtasks and attributed depending on their skills. The decision-making algorithms are often based on a multiple-criteria approach using a cost function, such as in [25], use Markov decision to determine the best execution plan [26]. Other allocation algorithms have been proposed to extend the task assignment scheme to the multi-human multi-robot context [27]. Authors in [26], [27] also took ergonomics into consideration when developing the task allocation scheme.

On the other hand, the principle of path planning algorithms is to generate suitable trajectories for the robotic arm by using, e.g. cubic interpolation functions, spline functions, or coverage path planning. Those solutions are often only valid for static environments, making them ill-suited for collaborative scenarios. The online method for constrained handling is traditionally to use closed-form laws such as potential field methods [30], or anti-windup strategies [31]. The former is able to avoid collisions by generating a field of repulsive forces around the obstacle, but is typically unable to deal with actuator saturation. The Model Predictive Control (MPC) is a general purpose control solution able to handle both state and input constraints in real-time. This method is based on the idea of solving at each time instant a constrained optimal control problem over a receding horizon. The disadvantages is the high computational load, although recent advancements in computational power have made it feasible to implement MPC on robots, MPC schemes are not commonly used in mechatronic applications due to their high computational cost and their need of having a precise model. Therefore methods as the Explicit Reference Governor (ERG) [32] can enforce both state and input constraints without having to solve an online optimization problem, so it can be computed real-time.

When applying task allocation schemes more criteria than the relative performance can be considered. These criteria might refer to reliability, number of personnel workload or safety [33]. Regardless of which criteria are used in order to apply a function allocation scheme, work designers have to be aware of the fact, that the “automation of functions may introduce new work tasks for the operator that are not directly related to any single function” [34].

HRC Flexibility

Cox Jr [35] defines manufacturing flexibility as “the quickness and ease with which plants can respond to changes in market conditions”. Hence, HRC flexibility is needed at two layers: to adapt to the aforementioned *manufacturing* *flexibility* typical for Industry 4.0 (due, e.g. to the variety of part shapes and weights, each with small batch size) and to adapt to the worker intentions and commands (which may vary from one person to the other). Several specific manufacturing applications are reported in the research literature, where cobots have addressed collaborative assembly of a homokinetic mechanical joint [36] and of cellular phones [37], among several others. Yet, all the above research works target specific applications, and it is rare to see a cobot capable of addressing multiple and diverse factory tasks. Ideally, such cobot should be mobile, dexterous, bimanual and easily reprogrammable. A platform developed with such flexibility in mind is the mobile cobot BAZAR [38] (see Figure 3), with its open intuitive programming software OpenPHRI [39], but this is still mainly a research prototype. BAZAR integrates a variety of hardware devices, an integration that is nowadays eased by the diffusion of the Robot Operating System (ROS, https://www.ros.org). Another example is the MOCA platform [40], whose advanced flexibility has demonstrated in manufacturing [41], teleoperation [40], etc.

Indeed, in the authors' view, ROS has been disruptive in robotics, making modular programming available to everyone and facilitating integration of software and hardware likewise. In this sense, ROS contributes to pave the way towards the sought-after "Graal" of HRC flexibility. ROS is a middleware, which provides services designed for a heterogeneous computer cluster, as those generally present in robot applications. These services include, among others:

- hardware device abstraction and control,
- implementation of common robotics algorithms (i.e., for mapping and navigation, perception, localization, etc) in C++, Python, and Lisp,
- a graph representation of the architecture of running processes,
- communication between the mentioned - both synchronous and asynchronous - processes,
- package management.

The ROS language-independent tools and most of its C++, Python, and Lisp libraries are open source software, free for both commercial and research use. Because of these open-source software dependencies, the main ROS libraries are supported only on Unix-like systems - typically Ubuntu Linux. The fact that ROS was designed with open-source in mind has spread it quickly throughout the robotics research community. More recently, ROS-Industrial (https://rosindustrial.org/) is succeeding in attracting the attention of industrials towards the features of ROS. ROS-Industrial - also open-source - extends the capabilities of ROS to manufacturing automation and robotics, by including libraries, tools and drivers for industrial hardware. Its focus is more on striving towards software robustness and reliability, which meet the needs of industrial applications.

While open source robotic hardware seems still utopic - particularly in the industrial context - the breakthrough of ROS and of ROS-Industrial as open-source platforms may substantially contribute to the flexibility of future cobots worldwide.

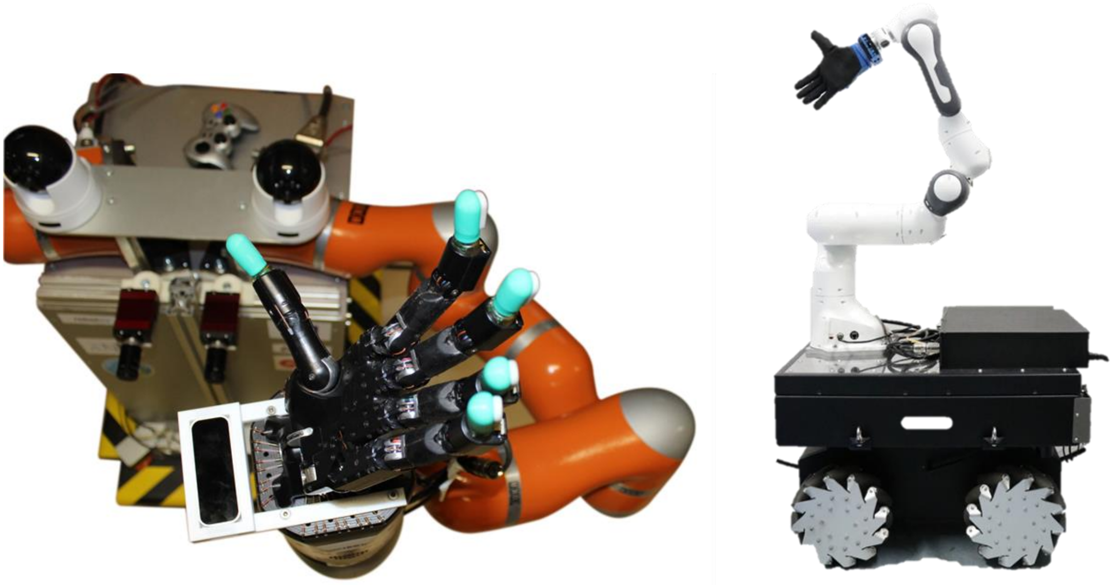

Figure 3. Top view of BAZAR (left) and side view of MOCA (right) robots. Their loco-manipulation capacities can add a certain level flexibility in manufacturing scenarios.

HRC Interaction Quality and Acceptance

When designing and introducing Human-Robot Interaction (HRI) to workplaces in a human-centred way, interaction quality plays a key role. Within dyads of humans interacting closely with robots there are several aspects that contribute to the quality of the specific interaction. One group of characteristics can be summarized under the concept of user-acceptance. The concept of technology user-acceptance comprises a rich research history. A number of theories and models bring forward different factors influencing the overall user-acceptance of a specific technology. These factors for example include aspects like “subjective norms” one feels are associated with the use of a specific technology. However, as shown in literature, the factors “perceived usefulness” and “perceived ease of use” have the strongest effect on users’ attitude towards a technology and should therefore be considered carefully [42], [43]. An additional fundamental aspect contributing to the overall interaction quality refers to the system’s usability. The ISO standard 9241-110:2019 (see Table 1) provides general design principles for system design that should also be considered in terms of HRI: The principle of "suitability for the task" refers to a meaningful use of the robot that is appropriate to the task. "Self-descriptiveness" includes the communication of the robot's mode of operation and current status, so that the human worker knows at any time what is happening in the interaction. The principle "controllability" describes the possibility of the worker to intervene in the process at any time and thus to maintain control over the robot. “Conformity to user expectations" means that the robot’s functionality is always in accordance with the expectations of the worker and the operational processes. The principles of "error tolerance" refers to two aspects. On the one hand it refers to false user input that can be corrected easily. On the other hand, it refers to the possibility of the worker to execute manual corrections in the task or process. “Suitability for individualization" describes the possibility of adapting the robot to the needs and abilities of the worker. Finally, the principle of "learnability" includes features that support or simplify learning how to operate the robot.

User-acceptance and fundamental design principles are major aspects that can be used in order to evaluate and to describe the HRI quality. There are additional factors that also contribute to the individual HRI quality experience. In addition to the principle of “suitability for the task”, special attention must be paid to the tasks remaining with the worker when tasks are divided between humans and robots. Thus, unfavourable tasks should not be delegated to the worker and a too tight coupling to the robotic system should be avoided. In addition, the process of introducing a robotic system should be carefully prepared. A detailed explanation of the purpose and benefits as well as the operating characteristics are just as much a part of this as the workers’ opportunity to address possible concerns related to the system. A reserved and sceptical workers’ attitude is not unusual and should be addressed in an early stage.

There is a limited but growing amount of research focusing on the experiences of factory workers who collaborate with cobots outside the lab (e.g., [44]). A cobot named Walt is integrated at the manufacturing floor of Audi for a glue operation, which has due to the noise in the factory, been equipped with non-verbal communication cues as ability to express emotions and understand gesture [45]. In terms of the social acceptance of the robot, the interviews performed at the end of the project with the operators who used Walt demonstrated that the robot had been accepted as part of the team. Furthermore, they mentioned that working with the latest technology actually gave them a sense of pride.

Table 1. The ISO standard 9241-110:2019 general principles for system design summarised in the table below.

ISO 9241-110:2019 General HRI principles for system design	
Suitability for the task	The meaningful use of the robot, which is adequate for the task.
Self-descriptiveness	The robot's mode of operation and its status is constantly given, so that the human worker is aware of the interaction situation at any time.
Controllability	The possibility of the worker to intervene in the process at any time to maintain control over the robot.
Conformity to user expectations	The robot’s functionality is always in accordance with the expectations of the worker and with the operational processes.
Error tolerance	False user input that can be corrected easily and the possibility for the worker to execute manual corrections in the task or process.
Suitability for individualization	The possibility of adapting the robot to the workers’ needs and abilities.
Learnability	The system includes features that support or simplify learning how to operate the robot.

HRC Standardization: Ergonomics

Prevention of work-related musculoskeletal disorders is possible by implementing ergonomic interventions able to improve workers physical conditions in manual handling activities such as heavy load lifting and handling low loads at high frequency. In the industry 4.0 era, designing appropriate and effective ergonomic tools means taking into consideration all the opportunities offered by technological innovation such as online instrumental-based approaches for biomechanical risk assessment and systems for evaluating the physiological and thermal impact of HRC technologies use. Furthermore, one of the challenges of the next few years will be the revision of existing ergonomic international standards and the development of new ones.

Online instrumental-based approaches make use of wearable miniaturized sensors for accurate and precise kinematic (joint range of motions), kinetic (forces and torques) and surface electromyography measurement (muscle behaviours) [6], [42]. These tools allow: i) direct instrumental evaluations of the biomechanical risk when traditional methods are not applicable due to their equations and parameters restrictions ; ii) the rating of standard methods when they are applicable. These methods also offer the possibility of classifying the biomechanical risk even in the presence of work tasks in which HRC technologies are used. In fact, the traditional methods listed within existing ergonomic international standards for manual handling activities (ISO 11228 1-2-3) do not cover the consideration of biomechanical risk detection when collaborative technologies in general (e.g., cobots, exoskeletons) are used. This gap, together with the need to strengthen the scientific basis on which the standards are based on [46], represents the reasons why existing standards should be supplemented, revised or, if necessary, new standards should be developed. The outcomes of HRC related R&D projects have significant industrial relevance. Generated knowledge should be transferred into related standardization activities. These standardization activities must have two main objectives: i) to disseminate (at an early stage) knowledge about relevant existing standards and standardization activities; ii) to assess project results and to analyse them for potentials to be transposed into standards or to be used as input into already existing standardization activities. These will contribute to fill the gaps among existing standards in the field of HRC.

In addition to repercussions on ergonomic standards, the use of collaborative technologies needs to be also evaluated about its impact on physiological and thermal workers response. In fact, while such technologies are considered a promising option in biomechanical risk reduction [47] in several occupational sectors, on the other hand their use requires considerations on their suitability, costs, effectiveness and impact on the occupational safety and health of workers. One of the most important open issues is, without doubt, the long-term effects of their use on human physiology. Objective measurements should be supported by subjective measurements aimed at testing the user acceptance of the collaborative technologies by using questionnaire or interview in order to investigate physical demand, constraints, perceived usefulness, ease-to-use, intention to use, performance, comfort or discomfort.

HRC Productivity

From an economical point of view, HRC systems have a great potential to increase productivity in flexible manufacturing systems. In many modern factories, the limitations of full automation have already been reached. Large industrial robot cells, autonomous conveying technologies, advanced sensor systems for visual control and guidance, etc. are state of the art. Nowadays the production of passenger cars, for example, is widely automated (approximately 90-95%) until the car reaches the assembly shop. At this final stage of production, still manual human work is dominating with a degree of automation not more than 10-20%. There are two main reasons: compared to all prior parts of the manufacturing process (press shop, body shop, paint shop) the variety and the filigree of tasks is much higher and therefore it demands higher skills and more flexibility from workers. It is either very complicated to fully automate such tasks (leading to high risks for downtime) or it is not cost-efficient because available technological solutions are too expensive to reach a reasonable return-on-investment (ROI). Hence, cobot systems with reduced complexity and lower costs may provide a potential solution for increasing productivity in such work systems by supporting some of the ergonomically heavy work of humans in an efficient way. This may reduce the number of workers needed for completing all assembly operations (= direct effect on productivity), but it is also beneficial for the remaining workers' health by preventing musculoskeletal disorders and increase production quality (= indirect effect on productivity) [48]. In any case, however, as highlighted above, HRC systems have to be designed according to basic ergonomic and safety principles and have to consider the needs of the human operators in order to solve issues instead of creating new ones, increase efficiency and really help workers and companies.

Conclusion

Collaborative robots have demonstrated a high potential in addressing the flexibility needs of the increasingly competitive industry. They can simultaneously increase productivity, and reduce work related musculoskeletal disorders, which represent the single largest category of work-related disease in industrial countries. This can contribute to economic growth and creation of better, healthier, and more attractive working environments for the future workforce. Because of this unique potential, the collaborative robot market grows on average by about 50% each year [49]. It is important to note here that traditional industrial robots are not in danger of extinction; they will continue to play an important role in manufacturing, mainly as full-automated systems. Their primary purpose is to make high volumes of goods quickly and cheaply, which however, comes with the price of reduced flexibility and costly re-deployment.

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