

Strategic Action Line LI6: Evolving and Resilient Production



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Abstract The objective of this chapter is to describe the strategic action line related to evolving and resilient production (LI6). In particular, this chapter proposes research and innovation priorities aimed at exploiting a high degree of machine automation and self-learning, with levels of autonomy and adaptive intelligence designed to facilitate the operators' job. From the work with cluster members, it emerged in particular that the following topics need to be studied and developed in the coming years: modelling and simulation for the design and management of production systems as well as hardware and software technologies for production system reconfigurability. The technology enablers are linked to the availability of smart modular devices that can be integrated wireless in a transparent, autonomous way, capable of monitoring and controlling manufacturing assets and products, and supporting decision-making, ensuring ready access to all necessary operational, configuration, fault and maintenance data.

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R. Fornasiero and T. A. M. Tolio (eds.), *The Future of Manufacturing: The Italian Roadmap*, Springer Tracts in Mechanical Engineering,
https://doi.org/10.1007/978-3-031-60560-4_10

Keywords Reconfigurable processes · Sensors · Digital twins · Smart inspection · Human–robot interaction

1 Introduction

The use of sensors, automated controllers and embedded systems has become an essential part of production systems. However, many industrial companies have rather chosen to develop a proprietary Intranet of Objects, focused on local, restricted and closed-loop scenarios. Yet, the changes that are required of companies depend on a greater and deeper interaction between the various parts of the factory, based on collaborative machine-machine and human–machine behaviours. The analysis of the information collected and exchanged will allow to evaluate the occurrence of modifications and adapt the behaviour of machines, ensuring optimization of efficiency even in variable contexts. This will in turn encourage the implementation of manufacturing intelligence, i.e. a self-aware production system, capable of evolving and resilient enough to defy the uncertainties of the context.

Collaboration and connectivity will result in large amounts of data that will need to be analysed in real-time or near-real time and to be converted for the mobile devices of the decision makers at both central management and plant levels. Manufacturing firms will have a competitive advantage over their competitors if they can perform real-time analytics on a large volume of data from business processes, products and management systems.

The objective of this strategic action line is studying a new generation of production systems that can evolve over time to adapt dynamically to the changing conditions of the context, which are determined by the turbulence of demand, the speed of technological cycles, the dynamics of the competitive situation, and also by the dynamics resulting from sudden changes, such as catastrophic events like pandemics. The new production systems should, therefore, be conceived like evolving and resilient ones thanks to a high degree of machine automation and self-learning, with levels of autonomy and adaptive intelligence to facilitate operators to a large extent. Priority research topics regard: modelling and simulation for the design and management of reconfigurable production systems with related hardware and software technologies. Technological enablers will be dependent on the availability of modular and intelligent devices integrated wireless in a transparent and independent way, capable of monitoring and controlling production assets and products, and of supporting decisions based on data related to the entire operational, configuration, failure and maintenance processes (Fig. 1).

This objective will be implemented through research activities on the following areas:

- **Reconfigurability:** Design and control of reconfigurable and modular production systems;

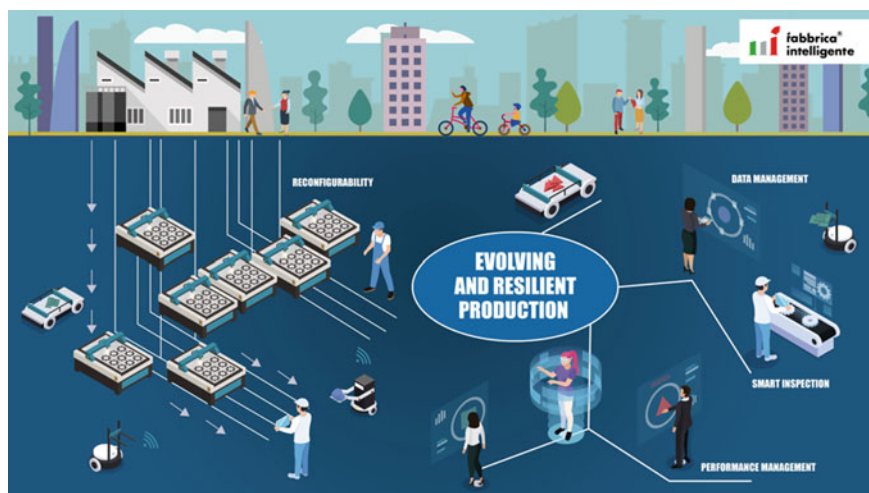


Fig. 1 Strategic Action Line 6—Evolving and resilient production

- **Components:** Components, sensors and intelligent machines for adaptive and evolving production;
- **Performance:** Systems for the prediction of manufacturing and logistics operations management and performance;
- **Inspections and data analysis:** Smart Inspection & Machine Learning;
- **Robot-human collaboration:** Human–Robot Co-working.

Artificial intelligence and related techniques will also have a significant influence in the development of each research and innovation priority.

Expected impact: improvement of the manufacturing sector’s capacity to adapt to the continuous evolution of technological, economic and market scenarios; improvement of the sector’s ability to respond to endogenous and exogenous shocks (from natural disasters to the temporary unavailability of critical infrastructures, from epidemics and health emergencies to contingent situations with a high impact on performance and continuity of operations); decrease in time to market; improvement of production factors’ efficiency; improvement of production control in real time/near-real time; improvement of system performance prediction capacity and greater human–robot collaboration.

The research and innovation priorities of the strategic action line on Industrial Sustainability are:

- **PRI6.1**—Design and control of reconfigurable production systems
- **PRI6.2**—Components, sensors and intelligent machines for adaptive and evolutionary production
- **PRI6.3**—Digital Twins for performance prediction and operational management of highly flexible production and logistics systems
- **PRI6.4**—Smart Inspection & Machine Learning

- **PRI6.5—Human—Robot Co-working**

2 PRI6.1 Design and Control of Reconfigurable Production Systems

The evolution of market and the speed of change in consumer needs are shifting mass production in favour of new products that can quickly meet immediate needs even when caused by disruptive events and trends related to product customization.

The new paradigm of competitive manufacturing will be redesigning assets adapting as promptly as possible to market changes, relying on an adaptive and resilient production system. The goal of this research and innovation priority is the study and development of technologies and algorithms for the design and control of highly reconfigurable manufacturing systems (i.e. easily integrated, adaptable and scalable).

Compared to the state of the art, the problem of reconfigurability must be considered at both machine and production line level, which involves the necessary development of advanced design, control and simulation systems and techniques that can adapt and optimize production models according to the product or the product mix.

The objectives of this research and innovation priority concern in particular:

- **Modelling and simulation.** To make the most of each factory's peculiarities, it is necessary to study and develop suitable software to speed up and improve the definition of the digital factory model and develop corresponding simulation environments, through procedures based on techniques of identification and adaptive recognition of the resources used in the production system—machinery, people, and materials. In particular, it is necessary to study new systems for the (semi-) automatic generation of simulation models (e.g. discrete-event simulation) starting from a digital model (“model-driven generation”), the use of simulation to support Artificial Intelligence generating synthetic data that can be used as training datasets. In every case, simulation draws the major benefits from the creation of accurate and constantly updated digital twins.
- **Methodologies for the design of evolving production systems.** In terms of design methodologies for production systems, it appears necessary to develop design techniques for production systems, such as, for instance, design for reconfigurability, design for maintenance, design for fast set-up and ramp-up, with particular attention to the design of systems for the production of unit batches and evolutionary systems.
- **Configuration of communication and data exchange architectures.** System configuration involves not only configuring the system's components but also the data architecture and data exchange systems among the different modules, which should be based on automatic transfer activity, such as to enable the configuration of the production system's data-model part.

- **Configuration of monitoring and control.** The reconfigurability of a production system requires adequate methodologies for configuration of a monitoring and control system that should adapt to the variability of applications and operating conditions. In particular, It is necessary to study and develop new methodologies for safe and remote commissioning of production lines when technicians can't be on site with the support of systems for the modelling, simulation, control and monitoring of the systems.

Interaction with Other Lines of Action

LI1—Personalised production: reconfigurability affords the necessary adaptability for personalised production systems.

LI4—High efficiency production & zero-defect production: a reconfigurable production system can adapt to varying operating conditions to achieve maximum efficiency at all times.

LI5—Innovative production processes: reconfigurability is frequently the key element for the development of new highly flexible production processes.

Time Horizon

Short-term goals of 2–3 years (starting from existing technologies):

- Solutions to simplify the definition of the digital factory model and corresponding simulation environments, through procedures based on techniques of identification and adaptive recognition of the resources used in the production system—machinery, people, materials, also aimed at remote set-up and control;

Mid-term goals of 4–6 years (significant development required):

- Advanced design and simulation technologies to translate product customization specifications into the design, production and development of the necessary machines and plants for those products;
- Configuration of appropriate communication architectures to integrate different control and data analysis functions;

Long-term goals of 7–10 years (requiring the integration of all the technologies developed by the research and innovation priority):

- Configuration of advanced monitoring systems for production plants, generation of dynamic digital twins with extensive use of machine learning and deep learning techniques.

3 PRI6.2 Components, Sensors and Intelligent Machines for Adaptive and Resilient Production

An adaptive and resilient production system requires new components that can detect and exchange data in an effective and intelligent way as well as new methodologies for managing collected and exchanged data which need to be integrated into the machines operating in the production plant.

Adaptive and resilient production systems will be characterized by multisensory networks for the supervision of processes and environments and for data collection. Increasingly sensitive and cost-effective sensors will facilitate the measurement of various process-influencing parameters, including on site measurements for process monitoring.

Sensor networks collect data that can be stored and processed near processes (edge computing) or uploaded to a private or public cloud network. Data must be available anytime and anywhere within the production system so that they can be processed through artificial intelligence systems, improving knowledge of a process at a systemic and detailed level.

The objectives of this research and innovation priority concern in particular:

- **Intelligent embedded sensors.** In order to improve the flexibility of the sensors used in machines, it will be necessary to develop techniques for miniaturization, which should lead to the generation of low cost sensors, with adequate energy autonomy and implementation of protocols for data communication. These innovations will be implemented on on-board sensors, equipment sensors, sensors on transport and handling systems and on the materials being processed. It is also necessary to research and develop sensors that can pre-process data on board data collection stations so that the processed data can be communicated to the control units and databases for the collection of the factory's big data, thus avoiding a redundant transfer of data.
- **Sensors and components for the Internet of Actions.** Development of sensors that can support remote actions, to avoid any loss of sensorial aspects, by enabling interactive and adaptive actions. Expert operators can thus operate remotely, getting around any limits to the mobility of individuals. In particular, the development of new sensors and actuators will be essential in creating a sense of presence when working remotely, as well as accurate and safe remote actions. In particular, new sensors and actuators that receive and reproduce tactile, visual, sound and olfactory signals are necessary. The devices used in IoA architectures must be designed to appropriately manage the interaction between the environment and humans and ensure the connection of devices present in the shopfloor to provide data on the status of ongoing processes. In particular, these devices should be suitable to handle a large amount of heterogeneous multi-source data, with adequate solutions to process the data streams with a view to extracting relevant information.
- **Universal intelligent gateways.** To increase the flexibility of machines and production lines, universal intelligent gateways need to be studied and developed and they should be vendor-neutral both in terms of transmission protocols

and in terms of the provided data formats. It will also be necessary to study new decoupling systems between the data measurement and collection part and the machines and plants control system.

- **Intelligent processing methods and tools.** To optimize the use of data generated by sensors, it is necessary to study and develop an adequate data collection and exchange infrastructure that can ensure data consistency and comparability. In addition, new protocols for accessing and recording data are needed, to implement large databases (i.e. big data) that are secure, persistent, resilient, modular and scalable.
- **In-process monitoring of sensors.** Precise and stable models for sensors and components need to be researched and developed, to ensure resilience and adaptability during the working cycle, with a view to approaching the process in a precise and deterministic way, to avoid deviation in the behaviour of the sensor or component from their model. Furthermore, using these models, and advanced machine learning and deep learning techniques, it will be possible to develop self-diagnostic strategies for the machine and, in the case of known and repetitive processes, predictive maintenance strategies.

Interaction with Other Strategic Action Lines

LI5—Innovative production processes: the new components and materials and the most effective sensors will forge intelligent machines to be deployed towards the design of innovative production processes.

LI1—Personalized production & LI4—High efficiency production: the new components will improve production systems, increasing both their adherence to individual needs (LI1) and their production efficiency, by reducing waste and defects (LI4).

Time Horizon

Short term of 2–3 years (starting from existing technologies).

- Methods and tools based on “Data Fusion”, “Machine Learning” and Artificial Intelligence logics for centralized data collection and processing;
- Tools based on innovative HMI and augmented reality able to simplify the corrective intervention by the operator.

Medium-term of 4–6 years (significant development required).

- New design methods for embedded sensors;
- Intelligent universal gateways that interface with sensor networks both at machine and at production system level;
- Integration of sensors that operate as distributed autonomous systems for the acquisition of data on the context, the machine and the production process;
- Methods and actuators for the implementation of adaptive and evolutionary behaviours at component/machine level.

Long term of 7–10 years (requires the integration of all the technologies developed by the research and innovation priority).

- Integration, at machine and process level, of “in-process” monitoring techniques for a closed-loop control of semi-finished/finished products’ quality and for the implementation of self-diagnostic and predictive maintenance logics.

4 PRI6.3 Digital Twins for Performance Prediction and Operational Management in Highly Flexible Production and Logistics Systems

The introduction of Cyber Physical System (CPS) allows the development of advanced and highly flexible production and logistics systems. With CPSs in the factory, shop floor control architecture for supervision in real/near-real time becomes feasible. This development is required by the current high product-variety trends, which result in a resource management complexity that has to be synchronized to the production-logistics system.

The “traditional” ability to manage and control the system in real time is supported by a new ability to predict performance in short-term decision-making (i.e., a few hours, several work shifts, a few weeks of planning) and supervision of decisions regarding operations. The use of Digital Twins (DTs) is a help in this context, for the processing of real-time/near-real time information from the field to support production control, in coordination with related activities such as maintenance, factory logistics, quality and others.

The potential of DTs in this area promises benefits in terms of enhancing system performance prediction capacities starting from constant monitoring of activities, in terms of ensuring the robustness of production programs in the face of process variability and frequent changes in workload conditions, and in terms of enabling a high response capacity to market needs while respecting production efficiency and costs. These features support the decision makers in the prompt evaluation of the various alternatives involved, so that they can select the best option in consideration of the system’s operating conditions.

The general goal of this research and innovation priority is the study and development of methodologies and tools geared to improve the use of DTs in real time/near-real time, for the ultimate purpose of exploiting their high potential for performance prediction and operational management of production and logistics systems with high flexibility.

In particular, the introduction of this type of DT is intended to complement existing architectures for the control and coordination of production, based on systems classed as Manufacturing Execution Systems (MES), and on advanced systems built with Internet of Things (IoT) infrastructures, introduced in order to integrate information on the state of the process, machinery and other resources involved in factory production and logistics also by applying Artificial Intelligence technologies for the

classification and prediction of the state of the processes, technical assets (such as machines, handling systems, equipment, ...) and the activities of the operators in the operating stations.

The objectives of this research and innovation priority concern in particular:

Integration of DTs with IoT platforms for monitoring the real state of the production-logistics system, and in general with standard connections and protocols to ensure communication with sensors and local controllers from the field, to improve the identification of the critical factors that emerge from the shop floor in relation to the status of the process, the machinery and other resources involved in factory production and logistics. In particular, these DTs must be able to generate a feedback on the system-control process and the related machinery and equipment in progress, and facilitate the synchronization of material flows in the Digital Twin's real time near-real time simulation.

Development of DT's advanced functionalities for the monitoring and analysis of material flows, starting from the logical and physical traceability of specific elements (the marking, labelling of products or, in general, from information collected through tracking devices).

Integration of DT with Artificial Intelligence (AI) techniques for the classification and prediction of operating conditions, state of health and future degradation of machines and other technical assets (with machine learning algorithms to support classification and prediction with a view to integrating the simulation capabilities of the DT).

Development of advanced functions in the DT for monitoring purposes and use of augmented intelligence in the execution of operators' tasks, to improve, including through AI techniques, a human-machine interaction in an increasingly close collaboration scenario, to optimize coordination and efficiency in the execution of operational tasks and facilitate operator productivity by mitigating the complexity due to the variety of products.

Integration of the DT with methods and tools to monitor and supervise production, to adapt the production program depending on the status of the process, machinery and activities in the various operating stations, to increase the robustness of performance in the face of process variability and frequent changes in workload conditions.

Development of advanced functions in the DT to monitor and analyse the sustainability of production technologies, to analyse consumption and limit waste of resources employed as part of a process of continuous performance improvement that combines DT simulation with "traditional" analysis techniques.

Eventually, the production-logistics system will draw overall benefits from the prediction, adaptability and resilience driven by a supervisory control in real time/near-real time, supported by the DT and by the systems backing operational decisions that are connected to it. In particular, real time/near-real time DTs for production-logistics systems will guarantee:

- Reduction of delivery lead times and reliability of production programs. Prediction, combined with optimization and verification of the variability impacts on system performance will allow greater confidence in achieving the objectives required by the supply chain in which the factory operates;
- Productivity and production costs, thanks to the optimization of the use of resources and of the execution of service activities (such as equipment preparation, material logistics, maintenance), while operating in conditions of variability;
- Higher product quality, thanks to the advance assessment of any process and machinery decay, in relation to current conditions and system prediction;
- Sustainability of production technologies, with the continuous improvement of performance and prediction of it;
- Operator productivity, taking into account its impact on system performance in ever tighter man–machine collaboration scenarios;
- Effectiveness of the decision maker’s task, thanks to the possibility of evaluating the trade-offs of different decision-making alternatives generated through the supervisory control of the system.

Interaction with Other Lines of Action

LI5—Innovative production processes: DTs should be developed in a way that is functional to technologies.

LI7—Digital platforms, modelling, AI, security: The technologies developed in the research and innovation priority can be applied to develop the platforms under LI7 and vice versa.

Time Horizon

Short-term goals of 2–3 years (starting from existing technologies).

- Integration of DT with IoT platforms for monitoring the real status of the production-logistics system
- Development of the DT’s advanced functionalities, to monitor and analyse material flows
- Integration of DTs with Artificial Intelligence (AI) techniques for the classification and prediction of operating conditions, state of health and future degradation of machines and other technical assets

Mid-term goals of 4–6 years (significant development required).

- Development of advanced functionalities in the DT for the monitoring and analysis of operators’ tasks
- Integration of the DTs with the methods and tools for monitoring and supervising production

Long-term goals of 7–10 years (requiring the integration of all the technologies developed by the research and innovation priority).

- Development of advanced functionalities in the DT for the monitoring and analysis of the sustainability of manufacturing technologies

5 PRI6.4 Smart Inspection & Machine Learning

Competition on global markets is determined by the possibility of ensuring, on the one hand, the quality of finished products and, on the other, the perfect efficiency of production systems, in a dual relationship in which the production system determines the quality of the product, while the quality of the product is evidence of the efficiency of the system. In an adaptive and resilient production system, the ability to verify production quality in a simple and intuitive way is essential, and smart inspection systems based on image analysis are the most attuned to this need. At the same time, the complexity of relations between system and product, in a context of continuous changes in products and operating conditions, can be managed through continuously adapting artificial intelligence systems that do not need reprogramming.

The goal of this research and innovation priority is the study and development of smart inspection systems and algorithms constantly connected to the production system. Compared to the state of the art, it is necessary to develop new smart inspection systems that can be intuitively programmed and that exploit the data exchanged in the factory to obtain a prediction of the quality of production while, on the other hand, helping to generate reliable information for the maintenance of the production system. This activity will have to allow a “Zero”-defects oriented strategy, with a production quality management that leverages the capabilities useful to other company areas, such as product design and machine design.

The main gap in state of the art systems is the lack of availability of smart inspection systems that are at the same time representative of a large number of product characteristics and that can be interpreted for decision-making purposes. For example, the development of supervised Machine Learning techniques, both predictive and classifying, should support the collection of information that comes from products and should automatically adapt to ever different products, without the need to be reprogrammed. Finally, it is necessary to develop advanced predictive maintenance systems that are related to production quality as well as to a machine’s sensor system.

The availability of reliable smart inspection systems will allow operators to enter controls online, increase production reliability and reduce costs and time to market at the same time.

The objectives of this research and innovation priority are:

- **Teach by demonstration.** Teach-by-Demonstration algorithms to programme collaborative and industrial robots, define sequences in an intuitive and yet robust way, in line with any constraints regarding system, product and interaction with the operator. Programming must ease high operational flexibility and avoid learning fatigue, through the implementation of human in the loop adaptation phases. The sequences have to be generalizable to adapt to different contexts. Efficient sequences should be implemented over a wide range of operational skills, including high-dexterity ones.
- **Machine learning for smart inspection.** Research and development of Machine Learning/Deep Learning algorithms is essential to ensure predictive quality to Smart Inspection systems. They would not only allow the correct classification of

product quality, but also the prediction of future events connected to the quality of the product, with a view to anticipating their occurrence. These algorithms must be able to optimize their parameters, adapting to different products and contexts, with no need to be reprogrammed. They should also allow an evaluation of the vision system while it is being designed and implemented, so that it produces as accurate a rating as possible.

- **Smart inspection systems.** Research and development of Smart Inspection and Machine Learning systems that can communicate with other interconnected machines, receiving information on format, material, operating conditions, or environmental changes, and automatically adapt their rating parameters to the changed production context and generate appropriate optimizations of the internal parameters. At the same time, the predictive capacity regarding specific product quality drifts must be used to activate predictive maintenance systems, to tackle the causes of subsequent defects.
- **Predictive maintenance.** Research and develop of advanced predictive maintenance systems that can collect data and signals, whether through passive systems based on embedded sensors, active systems based on the activation of specific components, or systems and analyses of the generated response. Such systems must be able to interpret the variability of the working conditions of the controlled organs according to the processes in progress, including by using environmental information (e.g. temperature, vibration), and information from Smart Inspection systems, for the determination of an optimal action time. The evaluation of the maintenance state of a complete machine system must be provided independently in terms of the estimate of the residual life of its elements, breakage likelihood, estimate of maintenance costs and potential obsolescence. It must be part of a general maintenance policy for the plant that allows to group individual actions and schedule them correctly for system management purposes.
- **Design of self-repairing machines.** In a medium-long term perspective, the integration of all the above techniques should lead to the creation of machines and systems with a capacity for self-diagnosis, remodelling and dynamic adaptation of process conditions, identification of maintenance interventions, choice of optimal strategies for intervention, automatic acquisition of replacement components, generation of detailed maintenance sequences, integration with augmented reality systems for operator or robot assisted intervention, self-checking, self-programming.

Interaction with Other Strategic Action Lines

LI4—High efficiency integrated systems & zero-defect production: Smart inspection systems can be exploited to implement high efficiency systems.

LI5—Innovative production processes: Smart inspection systems can be integrated into the development of innovative production processes.

Time Horizon

Short-term goals of 2–3 years (starting from existing technologies).

- *Teach by Demonstration* algorithms for collaborative and industrial robots that can program sequences in an intuitive and yet robust way, respecting the system, product and operator interaction constraints.
- Advanced predictive maintenance systems that can collect data and signals through passive systems, based on embedded sensors, or active ones, based on the activation of specific components and analyses of the generated response.

Mid-term goals of 4–6 years (significant development required).

- Machine Learning/Deep Learning algorithms for the predictive quality of Smart Inspection systems
- Smart Inspection and Machine Learning systems that can communicate with other interconnected machines.

Long-term goals of 7–10 years (requiring the integration of all the technologies developed by the research and innovation priority).

- Design of self-repairing machines, with self-diagnosis, reshaping and dynamic adaptation of process conditions, identification of maintenance actions, choice of optimal intervention strategies.

6 PRI6.5 Human Robot Co-Working

Today, collaborative robots are available on the market and provide safe interaction between humans and robots. However, the performance that can be achieved with collaborative robots is still limited.

Compared to the state of the art, this research and innovation priority is based on the fact that human–robot collaboration aims to optimize production and improve work quality to obtain robotic systems that make the work of operators easier and efficient.

The goal of this research and innovation priority is to promote the study and development of algorithms for human–robot collaboration in the context of production systems. The interaction between the operator and the robot must be efficient, natural and intuitive. Furthermore, robots should contribute to the improvement of working conditions, improving posture and relieving users of the heaviest tasks (e.g. lifting loads in excess of 10 kg).

The objectives of this research and innovation priority concern in particular:

- **Awareness.** Robots should be designed to be aware of the logistics and nature of its surroundings to optimise performance in human–robot interaction. It is therefore essential that robots process the data collected by on-board and off-board sensors to gain awareness of the surrounding environment and of the operator with whom it is collaborating. In particular, it is necessary to research and develop new sensors

and data processing algorithms to provide robots with a kinematic and semantic representation of the surrounding environment and of the operator. Robots and their control systems will thus be aware of the nature of and movement in their surroundings.

- **Task assignment.** To succeed in achieving optimal human–robot collaboration, it is essential to segregate as best as possible the tasks that each of them is expected to carry out during execution of a collaborative work. Task assignment and dynamic scheduling algorithms are required, in order to assign work to man and robot in an optimal way, depending on existing constraints (e.g. constraints related to the quality of work), required performance (e.g. minimizing execution time) and monitoring operations.
- **Rescheduling.** Collaborative robots work in a very dynamic environment and it is highly unusual that a movement planned at the beginning of a task can be completed without the robot having to stop for safety reasons. This behaviour leads to a decrease in performance, which in turn calls for dynamic rescheduling algorithms that can induce the robot to dynamically choose the best path to perform a task, thus avoiding unnecessary downtime, by relying on sensors' data and making a prediction of the behaviour of the operator (by means of AI algorithms).
- **Communication.** A user-friendly and intuitive human–robot communication needs to be studied to establish a natural and efficient collaboration. The operator would thus be able to adapt the behaviour of the robot to her/his specifications, optimizing the collaboration thanks to new multi-modal communication techniques between human and robot and create a gestural, vocal and physical interaction that maximizes the synergy between the two.
- **Quality of work.** Human–robot collaboration should be based on robots to improve the quality of the human operator's work, and new solutions for trajectory generation should take into account not only process performance, but should optimize the quality of the human operator's work (e.g. posture).
- **Collaborative Automation.** Building a collaborative robot is not enough if the cell that surrounds it consists of non-collaborative automation. Therefore, the concept of collaborative automation must be studied, and the automation needed for a safe interaction between man and technology must be developed. Only by using collaborative automation together with an intelligent collaborative robot will a collaborative work cell be possible.

Interaction with Other Lines of Action

LI5—Innovative production processes: the human–robot collaboration techniques developed in this research and innovation priority can be exploited for the development of innovative production processes.

Time Horizon

Short-term objectives (2–3 years) start from existing technologies to optimize:

- Robot's awareness of the surrounding environment;
- Rescheduling of the robot for unplanned program changes.

Medium-term objectives (4–6 years) require a significant development as regards:

- Separation of tasks between robot and operator to perform a work in a collaborative way;
- Systems to optimize the quality of work for the operator.

Long-term objectives (7–10 years) require the integration of all the technologies developed by the research and innovation priority in the short and medium term in order to improve:

- Communication to improve human–robot collaboration;
- Collaborative Automation to ensure that not only robots but also all the technologies within the factory interfacing with humans and robots are collaborative.

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