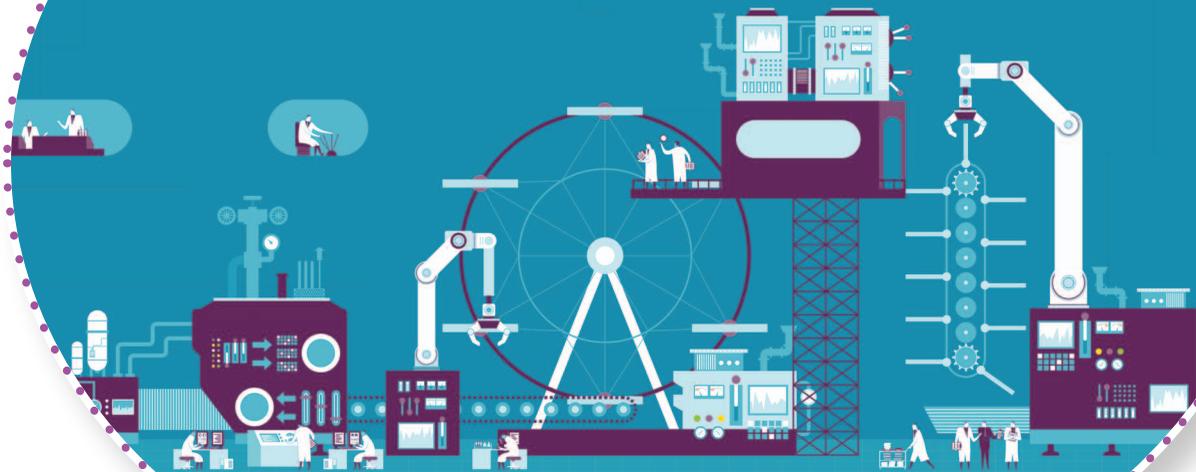# Smart Robots for Flexible Manufacturing

By Alexander Perzylo, Markus Rickert, Björn Kahl, Nikhil Somani, Christian Lehmann, Alexander Kuss, Stefan Profanter, Anders Billesø Beck, Mathias Haage, Mikkel Rath Hansen, Malene Tofveson Nibe, Máximo A. Roa, Olof Sörnmo, Sven Gestegård Robertz, Ulrike Thomas, Germano Veiga, Elin Anna Topp, Ingmar Kessler, and Marinus Danzer

Current market demands require an increasingly agile production environment throughout many manufacturing branches. Traditional automation systems and industrial robots, on the other hand, are often too inflexible to provide an economically viable business case for companies with rapidly changing products. The introduction of cognitive abilities into robotic and automation systems is, therefore, a necessary step toward lean changeover and seamless human–robot collaboration.

In this article, we introduce the European Union (EU)-funded research project SMErobotics (http://www.smerobotics .org/), which focuses on facilitating the use of robot systems in small and medium-sized enterprises (SMEs). We analyze open challenges for this target audience and develop multiple efficient technologies to address related issues. Real-world demonstrators of several end users and from multiple application domains show the impact these smart robots can have on SMEs. This article intends to give a broad overview of the research conducted in SMErobotics. Specific details of individual topics are provided through references to our previous publications.

Robots in SMEs

SMEs, i.e., companies with fewer than 250 employees, form the backbone of European industries, with over 1 million SME-level enterprises in the manufacturing domain [1]. They represent more than 99% of all businesses in the EU. In the past five years, they have created approximately 85% of all new jobs and provided two-thirds of total private-sector employment. The European Commission considers SMEs and entrepreneurship as key factors for ensuring economic growth, innovation, job creation, and social integration in the EU. It promotes entrepreneurship and supports SMEs through the Programme for the Competitiveness of Small and Medium-Sized Enterprises, which started in 2014 and will run until 2020, with a planned budget of €2.3 billion.

The International Federation of Robotics estimates that, for the major robot markets (apart from China), i.e., Japan, the United States, South Korea, and Germany [2], there are, on average, six robots per 10,000 employees in manufacturing SMEs. The average for all manufacturing industries is 246, with an average of 1,225 for the automotive sector [3]. These numbers indicate the huge market potential for industrial robots in manufacturing SMEs, which has not yet been adequately addressed. The products of manufacturing SMEs typically are very diverse. They employ a multitude of different technologies (e.g., welding) and different kinds of shape forming (milling, grinding, bending, and so on) and industrial assembly. But they share a common secret: the success of SMEs in Europe is based significantly on versatile production, close customer relationships, and the resulting ability to quickly react to changing demands in the market, as well as the ability to adapt to individual customer requests.

SMEs in contract manufacturing are characterized by frequent product changes and a broad range of product variants. Today's industrial robots have been designed for a different scenario: large-scale, high-throughput manufacturing systems that produce one specific product (or a small set of quite similar variants) at very high quantities and with constant quality.

This discrepancy in manufacturing requirements hinders the introduction of industrial robots into manufacturing SMEs. Matters are complicated by the fact that SME production, due to the need for flexibility and versatility, is less structured than, e.g., a fully automated car manufacturing line. Another complication is that small enterprises (with fewer than 30 employees) often lack a dedicated IT department that is able to maintain robotic workcells. Instead, they have a very lean business administration and

a workforce almost exclusively composed of highly skilled craftsmen and product engineers. Therefore, SMEs require highly versatile robots that are able to work symbiotically with skilled human workers. Robots must learn from their own experiences and benefit from their human coworker's domain knowledge. They must be manageable without profound expertise in robotics (Figure 1).

Challenges and Requirements

The Danish Technological Institute, a member of the SMErobotics consortium, interviewed 825 chief executive officers (CEOs) of manufacturing SMEs during 2015 and found that 89% of Danish companies with fewer than 34 employees have basically no automation at all [5]. This is despite Denmark having the world's fifth-highest robot density in the manufacturing domain [2]. Fifty-six percent of the CEOs felt that robots could not be used in their context, and 41% felt that their production volume was too low to warrant automation.

In another study of 846 manufacturing companies, the Danish Society of Engineers revealed that the major reasons for investing in automation were lower production costs (84%), fewer errors in the product (76%), and less waste (68%) [6]. The main barriers to automation were considered

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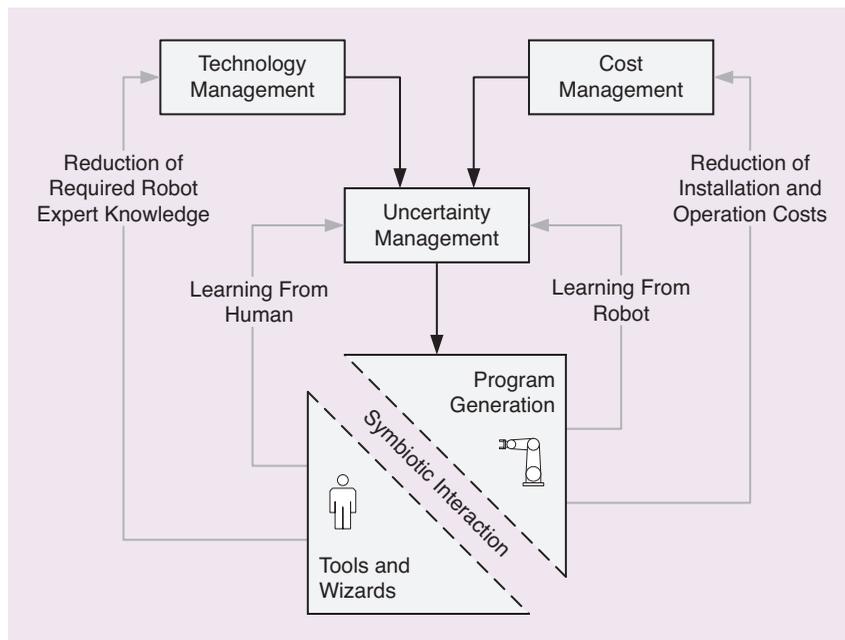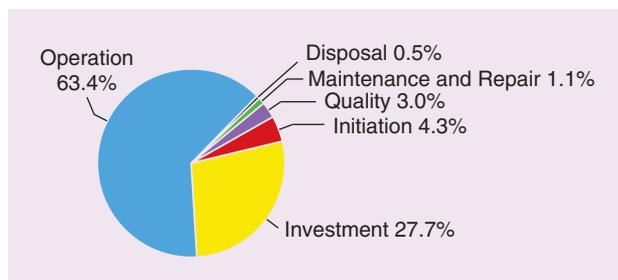

Figure 1. Automating complex manufacturing tasks necessitates managing the required technologies and associated costs. Uncertainties, e.g., deviations in the geometries of the work pieces or a drift in process parameters, counteract these management efforts. To cope with such issues, cognition and learning strategies are required on the robot side and the human side. Human operators need support through suitable software tools and wizards.

to be lack of time to obtain investment finance and implement changes in production processes and lack of knowledge and technical expertise among both managers and employees. A more considerate analysis of the study suggests that the main challenges preventing the use of industrial robots in SME manufacturing include the following:

1) Current robot programming techniques are not suitable for frequent changes of often highly customized products manufactured in small batches.
2) Tool-centered manufacturing processes require investment in robot-suitable tool replacements.
3) Classical robot cells with fences take up more space than comparable manual workspaces.
4) Formalizing implicit production knowledge into engineering specifications or robot programs is a difficult task.
5) Operating industrial robots is complex and requires expert knowledge in robotics.
6) Decision makers in SMEs lack expertise in robotics: they cannot properly assess the capabilities of robot systems or predict associated costs.

These findings are echoed in the euRobotics Multi-Annual Roadmap (MAR) [7]. The euRobotics MAR is a joint document created and continuously updated by the European robotics industry and various research organizations. It states that the main requirements of SMEs include the need to design systems that are intuitive to use and cost-effective at low lot sizes. This means that robot systems must be easily adaptable to changes in products or processes without the need to rely on extensively trained employees. As the total cost of ownership for an industrial robot is dominated by operational costs, e.g., for training of employees or for external programmers (Figure 2), such robot systems can help to effectively reduce overall costs.

SMErobotics Solutions

Overcoming the economic and technological challenges requires a new set of enhanced robot technologies that focus on intuitive human–robot interaction (HRI) and robust automatic operation. In the SMErobotics initiative's approach, HRI and robustness complement each other to form a cognitive robot system that addresses the main challenges described in the previous section. Intuitive HRI interfaces can improve the reliability of the system through human-in-the-loop decision making. The developed methods for uncertainty-aware robust automation not only enable the robot to perform more challenging tasks; they also increase the level of abstraction of decision making, further improving intuitive HRI.
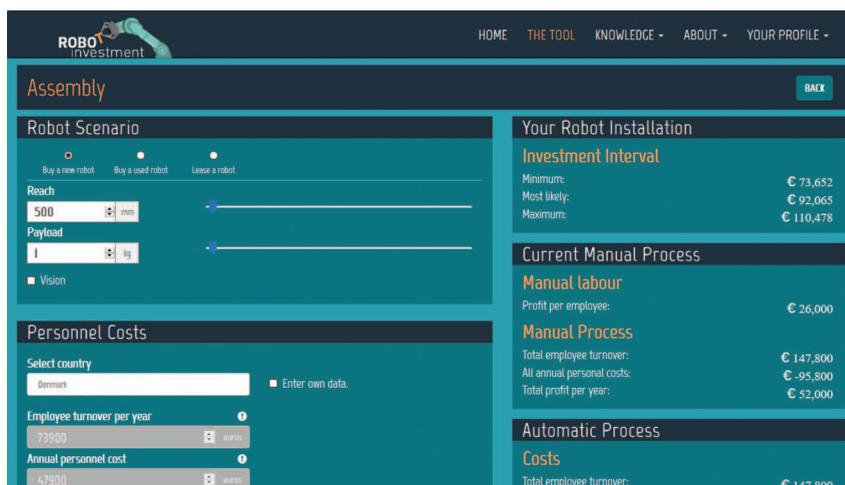
These concepts are built on top of a set of underlying principles, i.e., awareness of the environment and manufacturing context, knowledge- and sensor-based uncertainty handling, and efficient communication. The combination of these technologies within an integrated tool chain results in a cognitive system that complies with the needs of SMEs.

The following sections give a brief summary of the key approaches taken by the SMErobotics consortium and the technologies that have been developed by its members.

Investment Decision Support Tool

As observed during our user studies (see the "Challenges and Requirements" section), a major barrier that keeps SMEs from applying robotics technology is the uncertainty about costs. To mitigate this obstacle, we developed the web-based Robot Investment Tool (https://www.robotinvestment.eu/; Figure 3), which assumes that users do not know much about robots but do know their product: how much it weighs, how far it needs to be moved, and its overall shape and composition. Users know what kind of task they want to automate, e.g., arc welding, spot welding, grinding/finishing, painting, assembly, handling, packaging, or palletizing. They are aware of how many employees are required for the current manual process and the associated costs. Given an educated guess about how many employees will be needed to manage the automated workstation and the expected change in productivity, the SME receives an assessment of its business case. The

Figure 2. The distribution of total cost of ownership for a human–robot cooperation workcell [4]. Typical of such workcells is the dominance of operational costs in the overall balance compared with the actual investment.

Figure 3. An example calculation of the SMErobotics Robot Investment Tool for the assembly domain.

minimum, maximum, and most likely payback times are automatically calculated to estimate the range of investment depending on the exact system chosen. The calculation is based on figures from a number of system integrators, who have entered prices for software, hardware, installation, and person hours. Additionally, system integrators provide information about the robot type they recommend for various processes, reach, and payload.

The Robot Investment Tool enables SMEs to quickly and easily access knowledge about relevant robot installations and their estimated costs, while system integrators benefit from a higher visibility.

Seamless Integration of Production Knowledge

A key factor for cognitive automation solutions for SMEs is the integrated access to relevant data, such as process and product knowledge, hardware/software components and their capabilities, and workcell layout. In today's SMEs, production knowledge is often not formalized in a way that is suitable for interpretation by cognitive systems. In contrast to this, SMErobotics provides solutions for encoding and reusing knowledge to support the human operator in programming and handling robot systems.

Modeling Hardware/Software Components

Due to advances in sensor and tool technologies together with decreasing costs, more devices are constantly being added to robotic workcells, both to improve the manufacturing process through sensor-based adaptation and to facilitate easier programming of robots. To achieve this in an efficient way, an automatic or semiautomatic reconfiguration of the system is required.

Augmenting hardware and software components with semantic descriptions of their interfaces and functionalities enables self-describing systems. Connected devices can be automatically detected, and the resulting set of capabilities can be derived whenever a new component is added or removed. A model-based approach with a loose coupling of components and a semantic description of these components increases interoperability; i.e., it minimizes the required effort when combining hardware and software components from different suppliers.

Product–Process–Resource Technology Model

We have developed a model-based architecture for SME-suitable production systems that extends the well-known product–process–resource modeling approach [8] with a technology model [9] (Figure 4) that provides specific knowledge about manufacturing technologies, e.g., the optimal orientation of a welding torch relative to a work piece or parameters such as the typical voltage or wire feed speed for the given materials. In SMErobotics, these models are either serialized to Automation-ML [9] for higher compatibility with existing automation solutions or represented in a semantic description language (see the following section), which allows logical reasoning on the represented models to be conducted.
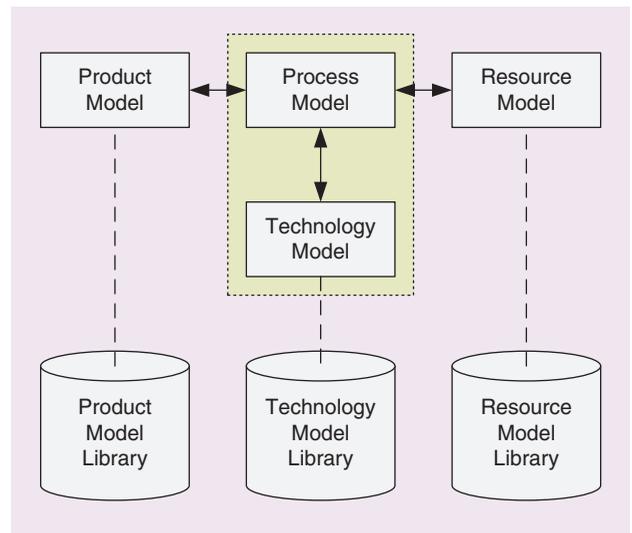
Figure 4. The extended product–process–resource modeling approach. Various types of models are created and (re)used for integration in an industrial automation solution. Process models reuse technology models to reduce the effort in parameterizing process steps. Process models refer to product properties and resources used in manufacturing the product.

Explicit Semantics

Separating knowledge from program code is a key motivation and design principle in our work. We create detailed models with explicit semantics for common-sense knowledge as well as domain-specific knowledge via ontologies [10]. Our semantic description language is based on the Web Ontology Language (https://www.w3.org/TR/owl2-primer/). Generic ontologies about common-sense knowledge such as data types or units are already standardized, e.g., the QUDT ontologies (http://www.qudt.org/). Basic ontologies for the robotics domain have been defined [11], but they do not consider the specific requirements of SMEs and their individual domains. We augment our base ontologies with domain-specific knowledge to create cognitive robotic systems specialized for a domain. Our semantic object model captures information such as mass, dimensions, materials, and boundary representation as well as their polygon triangulation [12].

> **A major barrier that keeps SMEs from applying robotics technology is the uncertainty about costs.**

Uncertainty-Aware Skills

In fully automated production lines, a major effort is required to minimize the location uncertainties of robots, tools, and workpieces. Robots are calibrated with an accuracy that is less than 1 mm and are typically rigidly fixed to the ground. The engineering costs required to achieve this are quite high.

Inaccuracies stem from inaccurate fixtures, the localization inaccuracy of active or passive mobile robot systems,
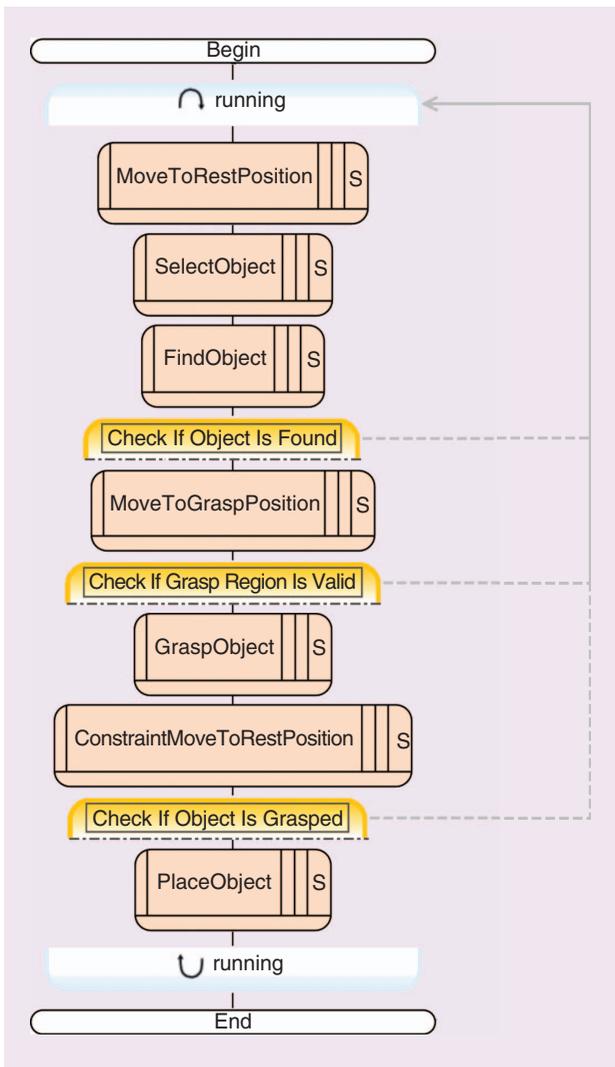
Figure 5. A graphical skill specification tool developed within the SMErobotics project. The displayed pick skill consists of a sequence of individual steps with conditional branches.
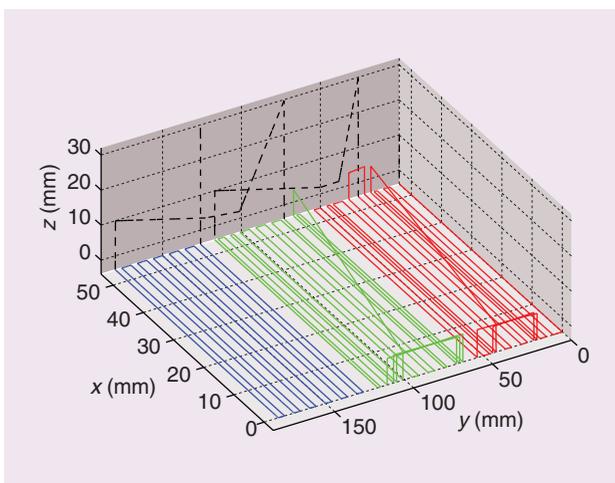
Figure 6. The learned milling path for pocket milling using an auto-training algorithm. Dashed black lines represent transitions between pockets. Each color represents a different milling path for an individual pocket.

or even inaccurate work pieces, e.g., bars that are manually cut to length. Robot programmers have to envisage the resulting uncertainties and their implications. The costs are then shifted from engineering to programming but still remain high.

The SMErobotics initiative's approach is to encapsulate the uncertainty handling within so-called skills, which can be parametrized and reused in different applications [13]. This reduces the programming effort for such tasks and relaxes accuracy requirements of part positions in the workcell.

Skills are basic operations that can be combined to form complex tasks. Depending on their reusability, skills can generally be divided into the following groups:
1) universally applicable skills
2) common skills for a certain application domain
3) specific skills for a range of products/single product.

Universal skills such as handling, picking, or placing objects (Figure 5) are relevant not only for assembly but for most other domains as well. A challenging and well-known problem is the peg-in-hole assembly operation, where a peg has to be inserted into a narrow hole via force control [14]. After implementing the skill once, it can be reused for a range of pegs and holes by adapting the parameters of the skill.

Learning-Based Cycle-Time Minimization

For automated machining processes, expenses can be greatly reduced by decreasing the cycle time of desired tasks. This can be achieved by adapting the machining feed rate in combination with intelligent path planning of the machining task. Path planning is a complex task, especially for woodworking operations, due to the nonisotropic properties of the material. We developed a learning-based approach for milling to effectively minimize the cycle time independent of a priori knowledge of the machining process [15]. Different coverages of the milling tool in different directions result in varying behavior because of the nonsymmetry of the tool's teeth and the material's properties. The milling strategy is determined such that it minimizes the time to mill and return to the starting side of the milling operation. It considers the effects of tool coverage and feed rate as well as the cutting direction of the tool. Figure 6 shows the learned path for a pocket milling task.

Anomaly Detection and Error Handling

A human-friendly robot system must be designed keeping in mind the possibility of faults and mistakes caused by either the robot or the user. From an operator's perspective, clear indications of (suspected) faults, their causes, and possible responses are crucial.

We combined Bayesian networks and extended Markov chains to automatically learn the nominal execution of a given process based on related sensor data and to detect deviations thereof [16], as shown in Figure 7. On detection of a fault, the system may use one or multiple modes of communication to indicate the problem, depending on the available hardware and the type of fault.
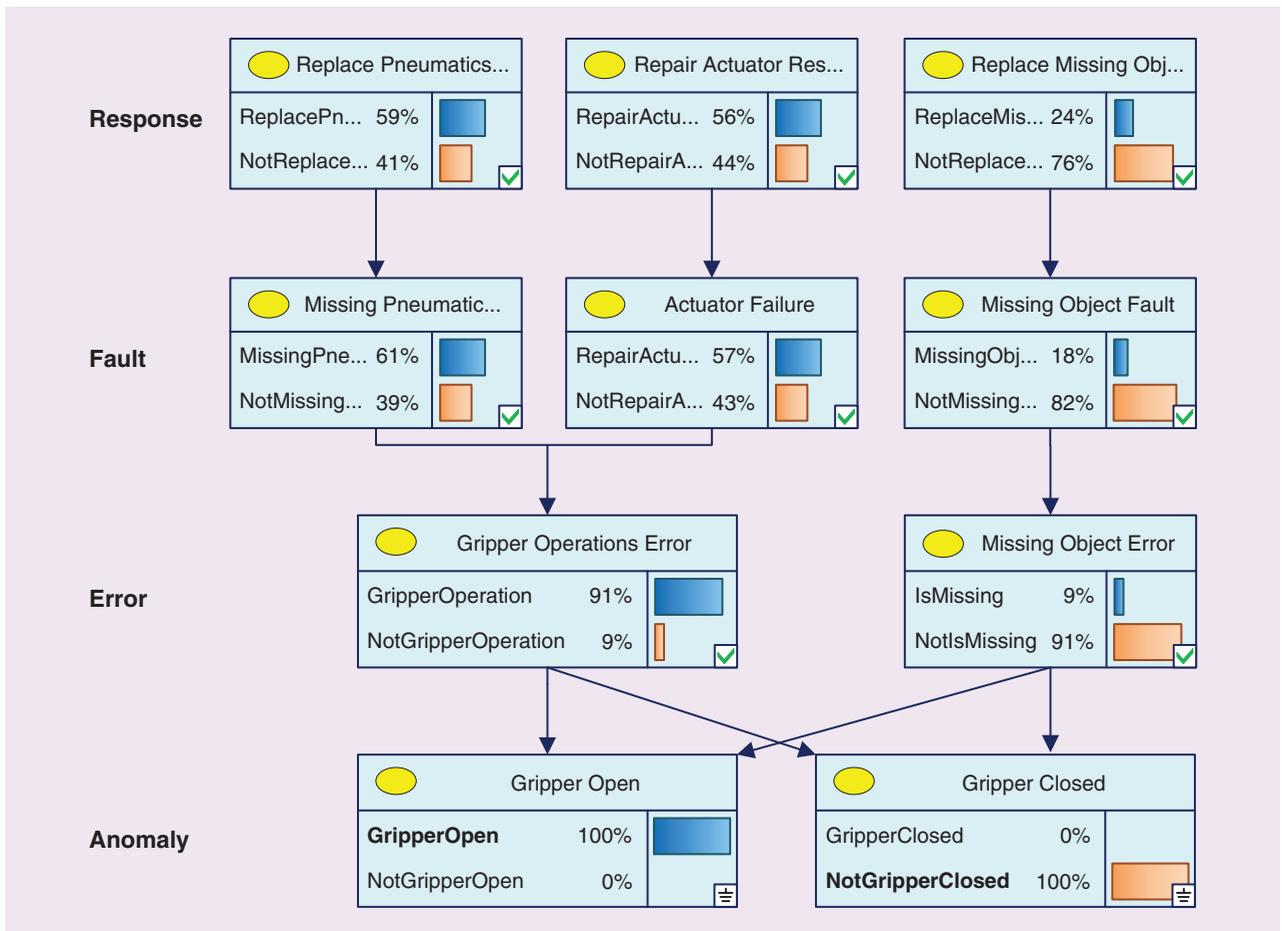
Figure 7. Given detected anomalies, the Bayesian network can infer the most likely causes. If response strategies have been modeled, these can be automatically executed with or without the involvement of the user.

Fault indications give general information like "Failed to grasp object X" and explanations of the faults' causes, e.g., "Object is out of reach" or "Gripper has failed to actuate." The user's responses are automatically learned by the system and stored in the form of updated probabilities and/or structural changes in the Bayesian networks. If previously learned, the system may suggest suitable recovery actions.

Product-Centric Instruction of Robots

Classical robot-centric programs define a sequence of functions that achieve a specific purpose, in the form of either text-based programs or graphical function blocks. Programming environments may combine this with CAD models of the workcell to use geometrical information in path definitions. In these approaches, the semantic context of the process is not encoded.

In service robotics, on the other hand, users specify the desired goal rather than manually program individual steps. In a similar fashion, we enable shop floor workers to instruct a robot in their domain language. The product-centric paradigm focuses on an abstract process definition that can be deployed on different workcells with matching capabilities without the need to adjust the process specification. Using our system's knowledge representation (see the

"Seamless Integration of Production Knowledge" section), the process is structured into a sequence of tasks that are mapped to a set of workcell-specific skills (see the "Uncertainty-Aware Skills" section) [13]. The system is provided with common knowledge, e.g., colors, units, and locations, as well as domain-specific knowledge, e.g., the types of tasks in a particular domain such as assembly or welding and their relevant task parameters.

We provide end users with domain-specific interfaces [17] that enable them to design their manufacturing process [10] with a direct connection to the semantic models of involved objects (Figure 8). To some extent, task parameters are automatically inferred from the selected object and the current context. Based on the requirements of the process and the capabilities of the workcell, the system uses logical inference and planning to generate a feasible task sequence for a particular workcell. In case of errors, the high-level task taxonomy is exploited to generate human-understandable feedback for the user (see the "Anomaly Detection and Error Handling" section).

Product-Driven Program Generation for Assembly

In contrast to large-scale automation with no variations, manual specification of robot programs or process instructions
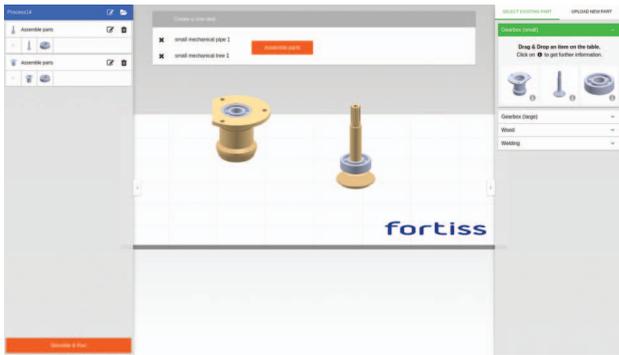
Figure 8. The intuitive web interface for industrial assembly tasks. The depicted example shows the first steps of a gearbox assembly process [Figures 10(a) and 11] on a virtual assembly table.

is no longer viable with a shift in market demand (e.g., individualized goods and other variants) leading to mass customization, thus affecting the manufacturing company itself and its production facilities, system architecture, and programming. paradigm.

For the domain of mechanical assembly, we developed an automatic assembly planner capable of exploiting product knowledge, i.e., using the 3D model of the desired assembly (Figure 9) as an alternative to a manual process specification [18]. The planner automatically generates multiple pairwise disassembly relations that, combined with information about forces and connectivity, lead to the creation of an AND/OR graph describing possible assembly sequences. A tight integration between the grasp and motion planner ensures that the subassemblies can be grasped and executed in the robot workcell. The grasp planner considers information concerning constraints and possible collisions with the environment as well as the assembly process and the joining action itself, while minimizing a desired objective function, e.g., the torque exerted on

the gripper. Based on this process, appropriate nodes of the AND/OR graph are pruned, resulting in a sequence of valid steps to produce the desired assembly [19].

To efficiently analyze the reachable workspace for a given robot, we further developed a motion capability representation. Feasible goal locations are precomputed offline and efficiently stored in a capability map [20]. As a result, the map can be efficiently queried online to determine the reachability of end-effector poses.

Evaluation in Real-World Demonstrators

A major objective of the SMErobotics initiative is to push its scientific and technological advances into actual production companies within a variety of industries.

To ensure this transfer toward real applications, four core demonstration partners tied to four major European robot manufacturers have been involved since the early stages when the core technological and scientific objectives were specified. Supplemental demonstration partners joined the project at a later stage via open calls [21] to evaluate the adaptability and versatility of the developed technologies in applications that were not precisely known during the specification phase.

SMErobotics results have been validated in real industrial settings through eight demonstrators covering three application domains: mechanical assembly [Figure 10(a)–(f)], welding [Figure 10(g) and (h)], and woodworking [Figure 10(i)].

Mechanical Assembly Domain

Dual-Arm Assembly With Product-Centric Instruction

In this demonstrator, a dual-arm Comau RML robot with two parallel grippers was used to perform a high-precision assembly of a mechanical gearbox [Figure 10(a)]. The workcell was
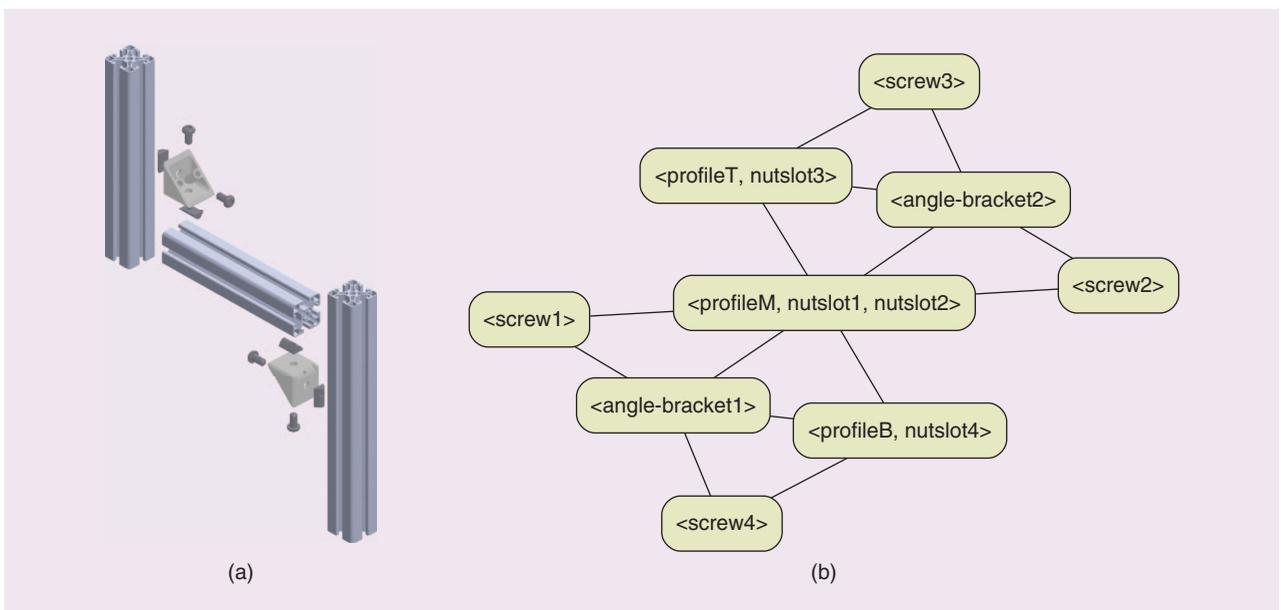
Figure 9. The desired assembly of aluminum profiles connected via brackets that are fixed by multiple screws and nuts. The CAD models serve as an input to the assembly planning component: (a) the exploded view of assembly and (b) the connectivity graph.

Figure 10. Demonstrators used to evaluate new technologies in the SMErobotics project: the (a) assembly of a gearbox, (b) assembly of a latch valve, (c) riveting for the assembly of custom grippers, (d) assembly of aluminum profiles, (e) assembly of high variants of valves, (f) subassembly of energy converters including tightening screws, (g) smart welding with automatic sensor-based path correction, (h) intuitive teaching of welding tasks, and (i) construction of a wall for a wooden house. [Part (b) courtesy of Tecnalia, Spain; part (c) courtesy of Kuka, Germany; part (d) courtesy of DLR Oberpfaffenhofen, Germany; part (f) courtesy of DTI, Denmark; part (g) courtesy of Fraunhofer IPA, Germany; and part (h) courtesy of INESC-TEC, Portugal.]
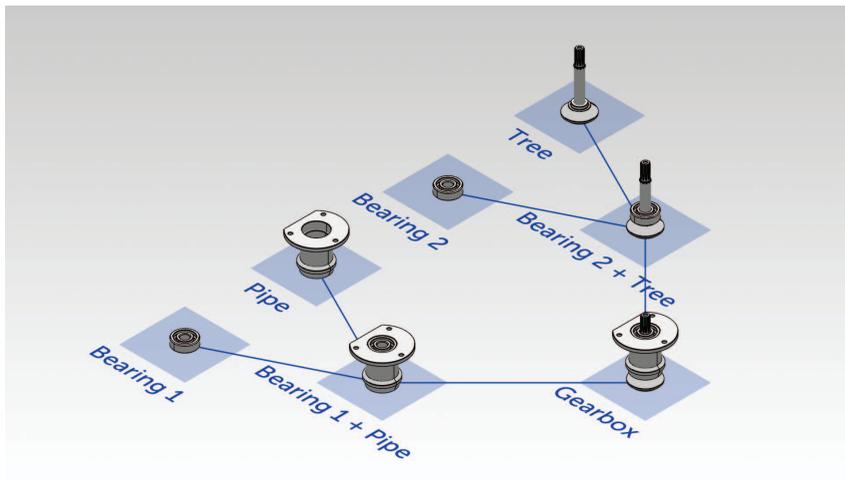
Figure 11. The assembly of the core element of a gearbox is based on four parts and performed in three steps. The first two steps are independent of each other, and the third step needs to be executed after the first two have been completed.

equipped with a camera for object recognition and a projector for highlighting detected parts on the work table. A high-level description of the assembly steps is shown in Figure 11.

For use in our product-centric instruction approach, we modeled a constraint-based assembly task based on a semantic description language (see the "Product-Centric Instruction of Robots" and "Explicit Semantics" sections). In this representation, valid assembly poses are represented by a set of geometric constraints between individual vertices, edges, or faces in the CAD models of two objects. Using an intuitive touch interface, the operator can instantiate the task for a particular pair of objects and input the required constraints (Figure 8). This approach is easier for workers to understand, compared with raw coordinates and Euler angles. The final process description consists of a sequence of tasks that is independent of a particular hardware setup. In a second phase, the process is deployed into a specific workcell. As our workcells are semantically described as well, we can use automatic reasoning techniques to check the compatibility of the process and workcell and infer additional tasks required for establishing this compatibility.

To evaluate our approach, we conducted a preliminary user study (https://youtu.be/B1Qu8Mt3WtQ) [10] that compared the time required to implement the assembly of the gearbox using our intuitive interface and using a teach pendant. The results are summarized in Table 1. Using our product-centric approach, we were able to achieve an 80% reduction in programming time.

Compliant Assembly of Loosely Supplied Parts

Our target application in this demonstrator is the assembly of 228 variant hydraulic valve sections consisting of the main body, spool, positioner, spring, O rings, and other parts [Figure 10(e)]. Due to the small tolerances allowed in this application, assembly strategies must rely on contact-based motions and the robot's programmable virtual stiffness. To handle the high number of variants, we implemented reusable skills, e.g., a force-enabled peg-in-hole skill that, in combination with the robot's compliance, enabled the system to successfully assemble the valve sections (https://youtu.be/IE9l-0rAMOiY; see the "Uncertainty-Aware Skills" section).

While the end user estimated that a cycle time of 5 min per valve section must be achieved for economic operation, the system was only able to achieve a cycle time of 15–20 min due to nonvalue-adding operations such as the preparation steps for loosely supplied parts, tool changes, and/or handling and clamping of components. However, the production quality was improved compared with manual assembly, resulting in fewer rejects. With an additional investment for dedicated screwdriver tools and feeder devices, the final production cell was able to achieve a cycle time lower than 5 min [22].

Automatically Planned Assemblies

Our use case in this demonstrator is the automated construction of different structures from aluminum profiles, brackets, slot nuts, and screws (Figure 9). Two compliant Kuka LBR iiwa robots are equipped with parallel grippers that can pick up an electrical screwdriver as needed. The individual parts are supplied through dedicated fixtures.

The desired product configuration has to be provided through either a 3D model of the final assembly or a demonstration by the operator (https://youtu.be/2jYhdmk-pMg). The assembly sequence planner then uses geometrical reasoning on the contained parts to generate a suitable sequence of operations that leads to the final product (see the "Product-Driven Program Generation for Assembly" section). Afterward, an algorithm maps the required sequence to executable robot skills. For this, we implemented a pick-and-place skill as well as force-enabled robot skills, e.g., for inserting the slot nuts into the aluminum profiles (see the "Uncertainty-Aware Skills" section). Complex operations such as the insertion of brackets require a coordinated, dual-arm skill, with one robot holding the profile and the other robot inserting the bracket.

Reliable Assembly and Screw Tightening

This use case deals with the assembly of a frequency converter [Figure 10(f)] in a workcell featuring a compliant robot arm, a flexible tool (consisting of a parallel gripper, screwdriver, and hand camera), and our Robot Co-Worker [23] skill editor (https://youtu.be/sgulAxn5-_o).

We implemented uncertainty-aware skills for snap-fitting parts and inserting screws (see the "Uncertainty-Aware Skills" section). The snap-fitting skill adjusts the robot's motion based on measured external forces on its end effector. For using the screw insertion skill, we need only specify the location of screw holes with a sufficient tolerance (in this case, only 0.5–1.0 mm). The compliant features of the robot arm, coupled with the torque control of the automatic screwdriver, enable reliable screw insertion using this coarse specification. In addition, we can automatically detect anomalous execution and use the operator's help to recover from it (see the "Anomaly Detection and Error Handling" section). Before each execution of a skill, the relevant object is detected using the robot's eye-in-hand camera.

Welding Domain

The two welding demonstrators share a similar setup. They both feature a 3D sensor for localizing parts and provide equipment for metal active gas welding. While the Reis robot [Figure 10(g)] has a 3D sensor mounted on its end effector, the Comau RML-based demonstrator [Figure 10(h)] has a sensor statically mounted in the workcell. The latter workcell additionally provides a laser line projector that is used to give feedback to the operator.

Uncertainty-Aware Welding Operations

Welding operations in SME-like manufacturing often face issues such as heat-induced bending of parts and large part variations due to the manual tack-welding of subassemblies. Errors in part localization or in the calculation of robot trajectories are also very common. To cope with these uncertainties, different solutions have been implemented for the two workcells.

Augmented Reality-Supported Welding

In this approach, we provide feedback to the user to validate upcoming welding operations before their actual execution. This validation can save a significant amount of rework. Based on the workcell's laser projector, we developed an augmented reality system that supports the user in intuitively programming the robot and validating beforehand the welding operations (see the "Product-Centric Instruction of Robots" section). The system highlights detected parts and related weld seams (Figure 12), allowing the user to adjust positions or alignments before the operation is executed.

Automatic Adaptation to Part Deviations

To automatically cope with geometric uncertainties, it is essential to accurately localize relevant parts and detect potential deviations of these parts from their ideal CAD models. For this, we implemented a welding skill that matches CAD data with point clouds from a 3D scan (see the "Uncertainty-Aware Skills" section). Like the correction of the robot path, the welding parameters can be adapted according to the detected deviations [24], e.g., in case of gaps, in the joint geometry. Figure 13 depicts the resulting weld seams with and without the compensation of assembly deviations.

Product-Centric Instruction of the Robot

In this experiment [Figure 10(g)], 13 weld seams on a previously tack-welded steel work piece had to be programed using our object-centric paradigm (see the "Product-Centric Instruction of Robots" section). The weld seams had lengths ranging from 90 to 480 mm. The evaluation of the required programming time for two test subjects—an SME shop floor worker and a robotics expert—indicate an increase in efficiency compared with a regular robotic welding cell (Table 2).

Woodworking Domain

Two experiments in the woodworking domain are based on an existing robot cell used by an SME to produce walls for wooden houses. The robot is a 6-degrees of freedom gantry system [Figure 10(i)]. Its workspace covers approximately
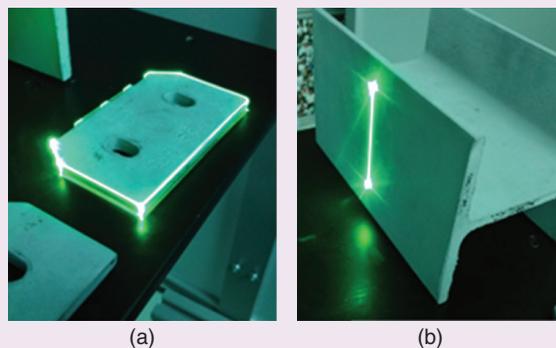

Figure 12. The augmented reality interface using a laser line projector to highlight (a) recognized objects and (b) features such as potential weld seams.
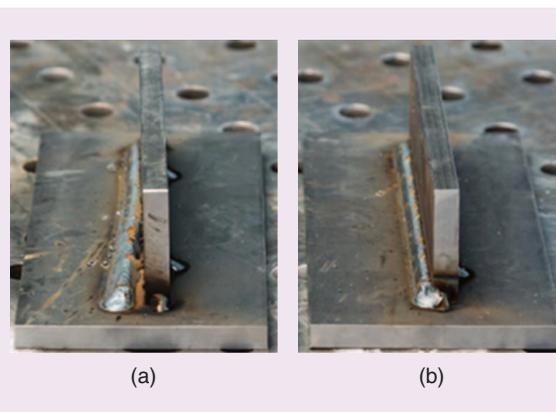
Figure 13. A welded workpiece (a) without compensation and (b) with compensation of assembly deviations.

Table 2. Evaluation of time (in minutes) taken to program individual steps of a welding process.

Process Step	Robotics Expert: Our System	SME Worker: Our System	SME Worker: Teach Pendant
Coarse teaching of welding poses including collision avoidance	0	0	117
Fine teaching of welding poses including collision avoidance	8.5	10	23
Parameter tuning due to false end-effector positioning	0	0	50
Calibration due to collision during programming	0	0	10
Total (without fixturing time)	8.5	10	200
Localization/fixturing of workpiece	2.5	4.5	n/a
Total	11	14.5	200 + fixturing time
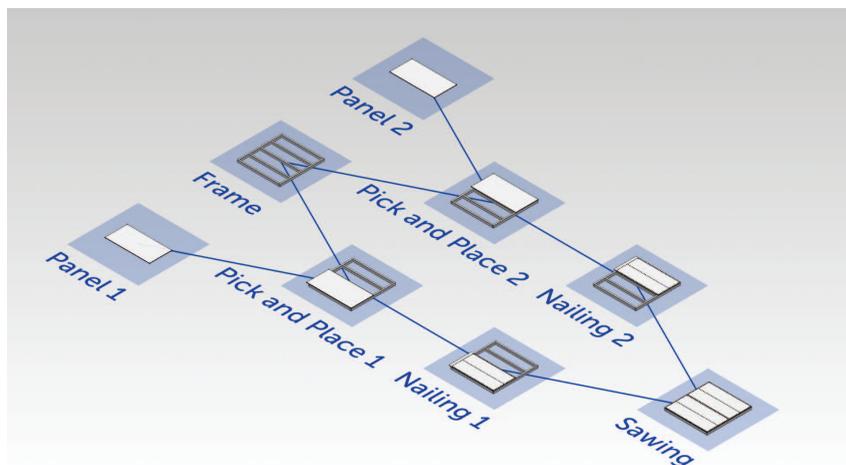
Figure 14. The assembly of a wall of a wooden house is based on a frame and two panels and is performed in five steps. The process involves picking the panels and placing them onto the frame. Subsequently, they are nailed to the frame, and the panels' overhang is removed through a sawing operation.

Table 3. Evaluation of time (in minutes) taken to program a woodworking process involving the construction of a wall.

Programming Assignment	Robotics Expert: Our System	Robotics Expert: Teach Pendant
Teaching new process (Figure 14)	13	47
Change order of process steps	0.2	1.6

30×4 m. Two robot-attachable tools can be automatically exchanged via a tool changer. The first tool consists of a rectangular vacuum gripper for picking wooden panels and an integrated nail gun, while the second tool is a circular saw. The workcell also features a dedicated measurement station that can be used by the robot to very accurately identify the orientation of a picked panel.

Product-Centric Instruction of the Robot

Based on our product-centric teaching paradigm (see the "Product-Centric Instruction of Robots" section), an expert in traditional robot programming was asked to instruct the robot to perform a specific task, as described in Figure 14. The expert has multiple years of experience in programming robots via a combination of teach pendant and CAD software but was a first-time user of our instruction approach. We compared the time required for creating the process description with the effort required to implement the same process on the teach pendant [10] (https://youtu.be/bbInEMEF-5zU). The results are presented in Table 3. The product-centric instruction approach yielded a 70% reduction in programming time.

Besides the constraint-based assembly task from the assembly domain (see the "Dual-Arm Assembly With Product-Centric Instruction" section), we introduced additional types of tasks to our framework: a nailing task, a sawing task, and a task for measuring the exact orientation of picked panels. Based on these tasks, the robot can be programmed on an abstract level for which the user defines instances of tasks that are inherently connected to the selected objects.

Exploiting the logical formalism behind our knowledge-based instruction approach, automatic reasoning is used to fill in gaps of underspecified process descriptions (see the "Explicit Semantics" section). For instance, specific actions such as the measuring of the position of picked panels are inserted automatically to ensure their exact placement.

Learning-Based Process Adaptation

For this experiment, we integrated additional sensors into the workcell to improve the sawing operations in terms of quality and cycle time (see the "Learning-Based Cycle-Time Minimization" section).

While sawing, the wear of the sawing blade and the path speed affect the quality of the cut. As the wear of the sawing blade gradually increases over time, the operator typically

lowers the path speed of blunt blades to achieve an acceptable quality. We evaluated several sensor modalities (audio, power, and accelerometer) to offer assistance in selecting the optimal path speed and determining when the blade is too blunt and needs to be replaced. By combining the different types of sensors, the developed wear-assessment component can distinguish between a reduction of the sawing blade's sharpness and the blade being warped due to extensive use. The latter condition could still occur after a blunt blade was resharpened [25].

Open Issues and Future Work

Introducing smart robots with cognitive abilities into robotic and automation systems is a highly challenging task and beyond the scope of a single project, especially for the agile production environments typically found in SMEs. Within SMErobotics, we identified the main challenges that currently impede the use of robots in SMEs and developed several solutions beyond the state of the art that lead to an increase in productivity and quality. Through eight diverse demonstrators, we showed that the solutions noted in the "SMErobotics Solutions" section are relevant and applicable across several domains.

Knowledge integration based on semantic models facilitates the formal description of relevant aspects of automation systems. Enhancing these models to fully encode the knowledge of a particular domain and the integration of more domains will be an important task in the future. Being able to handle uncertainties on multiple levels is essential in unstructured SME-like environments. Uncertainty-aware skills can provide the flexibility and adaptability required to realize processes previously deemed infeasible to automate. The use of the skill-based programming paradigm is slowly increasing in the industry, as indicated by a recent draft by the German Mechanical Engineering Industry Association (VDMA) of standardized sets of skills. These so-called VDMA companion specifications cover various domains, such as robotics or integrated assembly solutions. Our initial evaluations have shown that reducing the complexity of programming industrial robots is essential for financially viable small-lot production. More comprehensive evaluations must be conducted in the future to ensure that our concepts are suitable for a larger target audience.

Feedback from end users at the Hanover and Automatica trade fairs in 2014 and 2016 as well as the data from our Robot Investment Tool (see the "Investment Decision Support Tool" section) indicates a great interest in the topics of our project. To further facilitate the transition from traditional production paradigms to digital and robot-based facilities, EU-funded Digital Innovation Hubs are expected to provide easier access to technological facilities, expert knowledge, and educational and business support.

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