An Agent- and Role-based Planning Approach for Flexible Automation of Advanced Production Systems

Georg Weichhart
Flexible Production Systems
PROFACTOR GmbH
Steyr, Austria
georg.weichhart@profactor.at

Åsa Fast-Berglund
Industrial and Materials Science
Chalmers Technical University
Gothenburg, Sweden
asa.fasth@chalmers.se

David Romero
Center for Innovation in Design and Technology
Tecnológico de Monterrey
Mexico City, Mexico
david.romero.diaz@gmail.com

Andreas Pichler
Robotic and Assistive Systems
PROFACTOR GmbH
Steyr, Austria
andreas.pichler@profactor.at

***Abstract*—In this paper, we discuss the requirements for an agent- and role-based planning approach for flexible automation at advanced production systems. Special attention is given to balanced automation systems involving humans cooperating and/or collaborating with robots, and to processes interoperability between human agents and artificial (robot) agents towards flexible production system. This application context combines the research needs from fields of the Operator 4.0, Collaborative Robotics, Symbolic Artificial Intelligence and Automatic Control. We provide a brief overview of the contextualized state-of-the-art and discuss approaches towards flexible automation in advanced production systems.**

Keywords—Operator 4.0, Robotic Systems, Symbolic Artificial Intelligence, Automatic Control, Flexible Automation, Balanced Automation Systems, Cooperative Agent Systems, Production Systems, Processes Interoperability

I. Introduction

In the 1980s, *Computer Integrated Manufacturing (CIM)* used to focus on integration for reaching (cost) efficiency, which led to the vision of the "fully automated factory" [1]. Later in the 1990s, *Balanced Automation Systems (BAS)* tried to capture the idea of appropriate levels of automation when considering the challenges of flexibility, quality improvement and productivity as *ilities* [2] of advanced production systems; taking into account a balance between human and automation systems for the management and control of manufacturing processes [3] [4]. More recently, *Flexible Production Systems (FPS)* as manufacturing systems reacting in case of changes, whether predicted or unpredicted, have become to be on a growing demand, as companies transition themselves to become more agile. *Flexibility* becomes a critical production system *ility* to handle volatile market demands [5]. Moreover, *Intelligent Robotic Systems* capable of collaborating with humans (e.g. collaborative hardware robots (co-bots) [6] and collaborative software robots (e.g. chat-bots) [7]) will make a major contribution to FPSs. This desired *flexibility* will increase the management and control complexity of the production system. This in turn will decrease the *predictability* of the production system. To conquer this lack of predictability, *process-oriented approaches* have been created [8]. A *process* supports the orchestration of an "integrated system". However, processes are often pre-designed as "static workflows", which are executed at runtime. Thus, there is a gap between *flexibility* and *process-oriented execution* in production systems, when the system *ility* pursued is "flexibility".

In this paper, we discuss an approach that supports both, (a) *production processes* to orchestrate as an integrated system, and (b) a *flexible, modular production system* that can be re-configured on the spot. In order to have a well functional and flexible production system, it also needs to be "adaptable" to changes. This paper discusses an *adaptable socio-technical production system,* a flexible production system, seen from a scheduling point of view where the production resources are composed of both human and robot agents.

The overall planning approach for "flexible automation" needs to allow humans and robots, as *cooperative agents* [9], to understand the current production process they are working on, and the implications of sharing and trading tasks [10]. However, we have identified a number of assumptions. These assumptions make the constraints of the application scenario discussed in this paper explicit: "A flexible production system composed by human-robot collaboration workstations".

I. Task level synchronization is required for human-robot cooperation and collaboration:
   - Human and robot share tasks and synchronize task execution – they cooperate.
   - Human and robots co-exist, working on the same workpiece – they collaborate.

II. Non-routine jobs (still a set of tasks):
   - No static process design and description is sufficient.
   - Task(s) need to be communicated to humans and robots at runtime – however, model building blocks are *semantically clarified* outside our production system; *semantics* of individual tasks needs to be trained / taught before joining the system.
   - Automated planning and scheduling of production processes is required.

III. Performance improvement over time:
   - (Production) resource allocation should be done based on performance criteria such as competence, quality, speed and availability.

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- Learning and improvements by robots over time (e.g. Q-Learning) is at least desirable.
- Skill(s) improvement by humans over time is possible and it is assumed that the qualification of workers changes over time.

IV. Dynamic environment:
- Re-scheduling and re-planning of production processes and resources is required.
- Execution of planned production processes needs to be monitored and documented – in particular to understand deviations.

The first assumption (I) – as detailed above – specifies the level of granularity where *synchronization* takes place.

The second assumption (II) prompted this work in the first place. A stable environment would allow a process design, where roles and tasks of humans and robots are assigned, and processes are executed repeatedly. No automation would be necessary, robots and humans may be trained with respect to the overall process executed. Nevertheless, while the overall process and the task sequences change over time, the individual tasks have to be fixed in order to allow humans and robots to be prepared. There is training required, but it is on task level. The difference is that in a *static situation,* the overall process, including *synchronization points,* may be trained for the case of humans and for the case of robots can be programmed. In the *dynamic situation,* the task description (e.g. screwing), the production resources (e.g. screw M4, screwdriver) need to be known in advance. The process and task sequences are then dependent on the actual situation. This of course imposes a cognitive load on the worker, and robots need to be "intelligent and flexible", in other words, capable to react to changing tasks and to the worker [4] [6] [9].

However, in the third assumption (III), even with *non-routine jobs,* the individual task performance of workers will improve. Nevertheless, for the case of robotic systems, *flexible robotic systems* will be required for non-routine tasks; artificial agents (i.e. intelligent robots [6]) will need to be capable of learning and improvement over time (e.g. leveraging new possibilities provided by reinforcement learning approaches in robotics). This concerns the individual task performance.

The fourth point (IV) considers the overall production process performance. Partly implicitly driven by *non-routine jobs and manual work,* which results on a process execution that cannot be determined *en-detail a-priori,* since variations and improvements in task performance will have an impact on the overall process. This includes also situations where it needs to be determined if all tasks have been executed and if all tasks have been executed correctly. Such situations will require additional work-steps.

In a non-competitive environment, a plan with spare time would be sufficient, but in the highly competitive reality, cost and time constraints must be addressed, so re-planning and re-scheduling are required. Thus, monitoring of task execution is necessary to understand if everything is being done correctly. Of course (as a side effect), such monitored execution may be used to document the actual executed process.

The remaining paper is organized as follows. First, we identify the human and automation systems, and production resources involved in a flexible production system. This is followed by a discussion of different aspects when planning, automatically or manually, production processes for human-robot collaboration. We conclude with a brief outlook on a future balanced automation system supporting processes in human-robot collaboration.

II. Resource Allocation and Planning

In order to make the system *flexible* in terms of production resources and route flexibility, an *agent-based system* can be used in order to allocate tasks between different resources [9]. Task and resource allocation has been debated since the MABA-MABA list was published in 1951 [11], but since then new kind of resources and tasks allocation strategies have been developed, such as the *Operator 4.0* [12] and *Collaborative Robots* [6], as the two production resources that will be discussed in this paper, as well as new trading and sharing control strategies [10].

A. The Operator 4.0

The *Operator 4.0* can be defined as "a smart and skilled operator who performs not only – 'cooperative work' with robots – but also – 'work aided' by machines as and if needed – by means of human cyber-physical systems, advanced human-machine interaction technologies and adaptive automation towards 'human-automation symbiosis work systems' "[12]. In order to perform different tasks in these joint cognitive or physical systems, eight different interactions between the operator and cognitive and physical automation has been identified [12]:

1) Operator + Exoskeleton = Super-Strength Operator (Physical Interaction)
2) Operator + Augmented Reality = Augmented Operator (Cognitive Interaction)
3) Operator + Virtual Reality = Virtual Operator (Cognitive Interaction)
4) Operator + Wearable Tracker = Healthy Operator (Cognitive and Physical Interactions)
5) Operator + Intelligent Personal Assistant = Smarter Operator (Cognitive Interaction)
6) *Operator + Collaborative Robot = Collaborative Operator (Physical Interaction)*
7) Operator + Social Networks = Social Operator (Cognitive Interaction)
8) Operator + Big Data Analytics = Analytical Operator (Cognitive Interaction)

The *Operator 4.0 typology* [12] describes how Industry 4.0 technologies can cooperate with operator rather than compete as in the MABA-MABA list. Within this list, automation assists operators to become cognitive and/or physically more effective and efficient. Within this paper, we will focus on *Type 6 – The Collaborative Operator.*

On an abstract level, collaborative robots (co-bots) are capable of performing a variety tasks and that have been specially designed to work in direct cooperation with the operator. This includes intuitive interaction technologies, and shopfloor based teaching of robots without the need of programming skills [12].

In addition to this, some new ways of interaction are possible if the operator has its own intelligent personal assistant, as envisioned by the *Smarter Operator* [12] mentioned above (i.e. a soft-bot [7]). However, both is possible, a robot capable to directly interact with non-technical staff (i.e. teaching instead of coding), and a robot that supports indirect interaction through the digital agent of the user.

Independent of the way to interact with robots, there are different levels of how tight the activities of humans and robots are coupled and the level of granularity of *synchronization.* This is presented in the following section.

B. Degree of Coupling in Human-Robot Collaboration

In the last decade, *collaborative automation continuums* have appeared in manufacturing [13] [14] [15]. The interaction between the operator and the robot can be then defined as four different levels depending on the degree of human-robot interaction [16] [17]:

- *Co-existence* – The lowest level of interaction between operator and automation. The human and robot are separated by distance. The robot has no cage surrounding it. A coordinated interaction is necessary if robot and humans co-exist in the same space. This requires some form of collision avoidance and hence a simple form of synchronization of the executed tasks.
- *Synchronized* – The human and robot share workspace and workpiece, but perform their work at different times. Human-robot cooperation exists if both agents work on the same workpiece. This requires fine-grained task synchronization with respect to place and timing of execution.
- *Cooperation* – The human and robot perform work simultaneously, but on different workpieces.
- *Collaboration* – The most advanced and fine-grained form of task interaction is "collaborative robotics", where human and robot share workpiece, workspace and perform their respective tasks simultaneously. For this work on processes that involve human and artificial (robot) agents, both agents – on the fly – determine and synchronize who is executing what task. This includes situations where both agents work on the same task at the same time.

In many cases, if a robot breaks down an easy solution is to use human operators as a replacement resource. Unfortunately, if the different alternatives have not been considered during the process design the re-allocation of operations is not easy to perform. To tackle this issue, we suggest *agent-based systems* that keep track of alternatives according to different resources [18] [19]. Depending on what degree of interaction the operator and that automation will have, different resource allocation solutions needs to be analyzed. To be able to synchronize tasks of the involved human and artificial agents, a *process model* is needed that provides a description understandable by both [20].

III. Process Representations

In this section, we discuss different aspects of using procedures and process management, ranging from design and planning of processes, via the *communication* of these to the participants, to the executed workflow in connection with information systems and databases of the company.

Processes are used to coordinate the activities of different people having different roles in different departments [21]. *Procedures* are executed regularly by a group of people in organizations. These individual procedures often result in data or documents being produced and transferred to the next role. Making individual activities explicit in "process models" it is possible by communicating the *workflow* to other organizational members. This allows to the members of organizations to gain a common understanding of what is done in different parts of the organization, when working towards a common goal. Such explicit models allow improving and optimizing processes and share the explicit work knowledge and overall this supports organizational learning [22].

For the envisioned *process management system,* and its requirements, it is necessary to look on how processes are used by human and artificial agents. This includes finding an approach that allows humans and robots to understand the current process.

A. Business Process Management

Business Process Management (BPM) approaches have been created to drive the work of humans in organizations [21].

The *Business Process Modeling Notation (BPMN)* is a well-known approach. Version 2.0 has been accepted as an ISO standard [23]. *BPMN* takes a birds-eye view, and allows providing a *process description* based on organization roles that are first modelled as lanes. While on the positive side, BPMN is a large and feature-rich modeling language, this feature richness provides problems in practical environments. The exact semantics of the model elements are not clear, and on the pragmatics side, the correct usage elements is unclear [23]. Existing execution and workflow engines are capable to execute only a limited set of concepts. Processes modelled in BPMN are hard to be translated so that these can be executed automatically [24]. The code is also dependent on the workflow engine.

Fig. 1 shows a simple BPMN diagram with two roles. The green circle is the start event. Blue boxes are activities. Red circle is the stop event. Yellow diamonds are decision points (XOR). Messages (envelopes) are used to transfer the control flow from one to the other point [25].

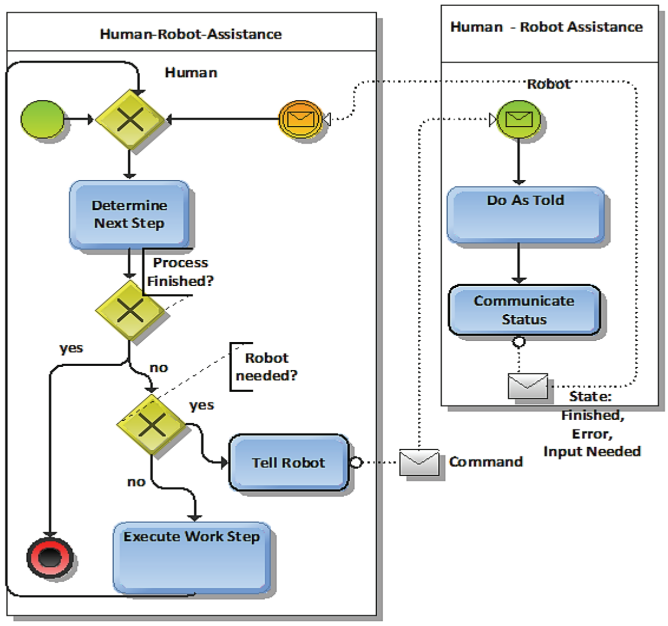

Fig. 1. BPMN Model involving Human and Robot [25]

Moreover, *Subject-oriented Business Process Management (S-BPM)* builds on two types of diagrams, i.e. two conceptual levels. At the first diagram, the individual behavior of roles, the *Subject Behavior Diagrams (SBD),* are specified. Then, roles (subjects in terms of S-BPM Lingua) are connected to other roles via the use of messages, implemented as send and receive states. The second type of diagram allows to model subject-interaction. *Subject Interaction Diagrams (SID)* show the message flows between subjects and conceptualizes the network of subject interaction. Unfortunately, this interaction model does not allow to specify protocols as detailed as in FIPA (Foundation for Intelligent Physical Agents) [26]. These two diagrams are on two different levels of abstraction and allow for different subject implementations with the same message based interface.

Furthermore, Fig. 2 shows three diagrams [27]. First, the two subjects exchanging messages diagram, then on the left the SBD of the worker subject, and on the bottom right, the SBD of the robot subject.

Yellow boxes are activities (with the circle and the "play" triangle is the start; with the square is the stop activity). Red boxes are receive states. Green boxes are "sending" states.

S-BPM has a well-defined semantics and a formal basis [21]. A formal implementation of S-BPM exists [28], which is based on *Abstract State Machines* [29]. As such, it may be used to describe the behavior of human and artificial agents [25]. Humans can easily understand the S-BPM as it has a focused set of symbols. The well-defined implementation supports for automatic control.

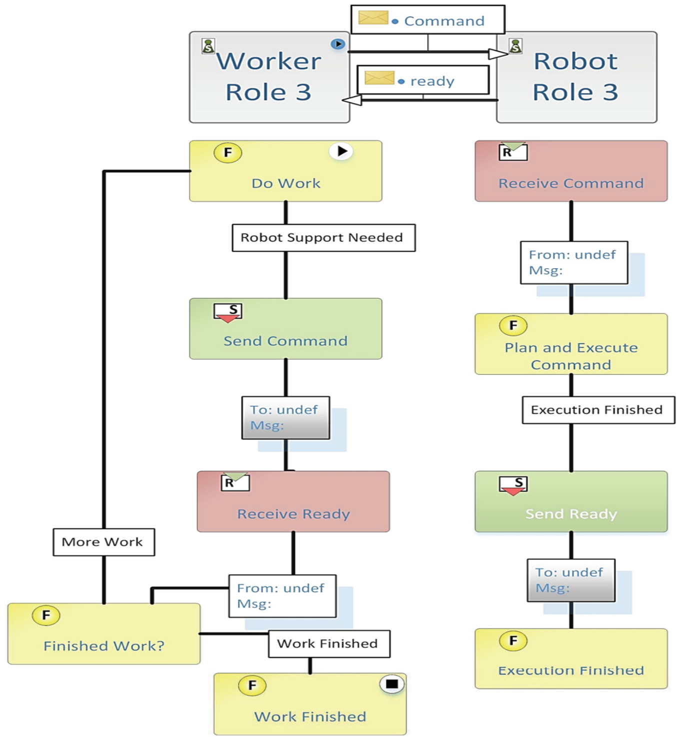

Fig. 2. S-BPM Human-Robot Collaboration Example [27]

B. *Analysis Methods for Tasks, Functions and Resources*

In the area of human factors and socio-technical research, two methodologies has been used in order to determine the task and resource allocation; the *HTA (Hierarchical Task Analysis)* developed in 1971 [30], and the *CTA (Cognitive Task Analysis)* developed in the early 90s. HTA is more focused on the goal, i.e. to assemble a part while the cognitive task analysis uses a variety of interview and observation strategies to capture a description of the knowledge that experts use to perform complex tasks more on the operators [31]. These methods are used to try to create a good task and resource allocation at the system, and to support operators to reduce their cognitive load. An important challenge, when designing balanced automated assembly systems using human and robots is to specify the order of tasks to be executed. Allocation of tasks usually happens later in the production system development, often during system implementation [32]. That allocation is often done "static". This is a global optimized distribution of tasks to resources, assuming everything works as expected. *Resource allocation* or *product/resource mapping* means that one or more possible production resources are identified for each operation/task. *Resource allocation* between humans and robots is a complex issue. Wo/man and machine should be seen as *complementary* resources rather the *conflicting* resources when designing a human-machine system. Robots and human operators sometimes have the same abilities, but in many cases, their abilities and capabilities are different. If they do not have the same abilities, then the matching between resources and operations is simplified. The desired degree of *flexibility* will inform the number of alternative resources that are included in this resource allocation. A final choice has to be taken by *optimization algorithms* [19].

Two examples where resource allocation has been used between humans and robots are given below. They tried to solve it in two different ways. Tan et al. used HTA [13] while Provost uses SOP [18].

Tan et al. also use the HTA with the idea to assign the human operator only to focus on tasks that required human skills and let robots handle all tasks that able to be automated (see Fig. 3). The result determine what and who should do it but not how and what tools to use, this can be further analyzed with analyzing different *Levels of Automation (LoAs)* [33].

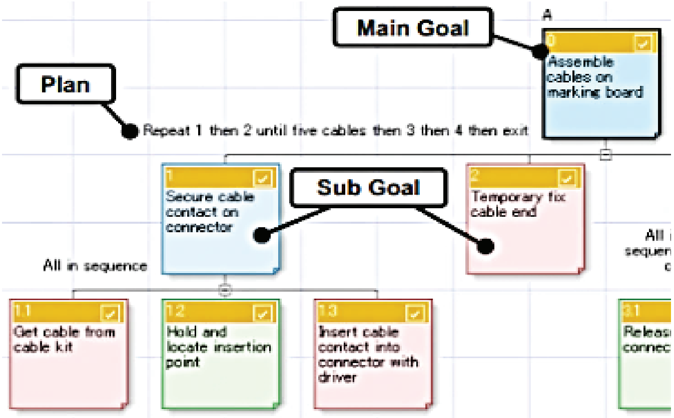

Fig. 3. Resource Allocation Planning using HTA. Human-Robot: Blue; Human: Pink; Robot: Green [13]

SOP is a graphical language describing the operation [34] (or Task if referred to the HTA). Each operation includes a set of conditions, describing when and how the operation will execute. This language was mainly use solely for robots, but Provost et al. [18] tried to combine the SOP with competence matrix in order to include also humans as possible resources. In this approach, a task optimization is performed taking into account all pre- and post-conditions except those related to resource booking. Then, each operation is allocated to a set of alternative resources. When it is possible, alternative resources should be chosen among different LoAs [33]. Fasth et al. [33] describes three approaches with regard to how they handle tasks and resources:

1. *Global Optimization* (containing both tasks & resources) as illustrated as X in Table 1, which is informed by Fig. 4. The needed tasks and the needed resources are optimized at the same time according to some constraint, often in terms of cycle time.

The two other approaches are divided into "2a" and "2b", because the *task optimization* is the same, but the local task allocation differs.

2a. Task optimization and local resource allocation with resource alternatives (i.e. redundancy) (illustrated as Y).

2b. Task optimization and local resource allocation *with prioritized resources* (ranking of the resources (R1-R5) from 1 to N, where N=4).

TABLE I. COMPETENCE MATRIX [18] AND [32]

Task/ Resourses	R1	R2	R3	R4	R5
Place A	XY1	Y2		Y3	4
Place B	Y1	XY		Y3	4
Fixate A			XY1		
Fixate B			XY1		
Assemble A+B	4	Y3		XY1	Y2
Inspect A+B	Y1	4		X2	Y2

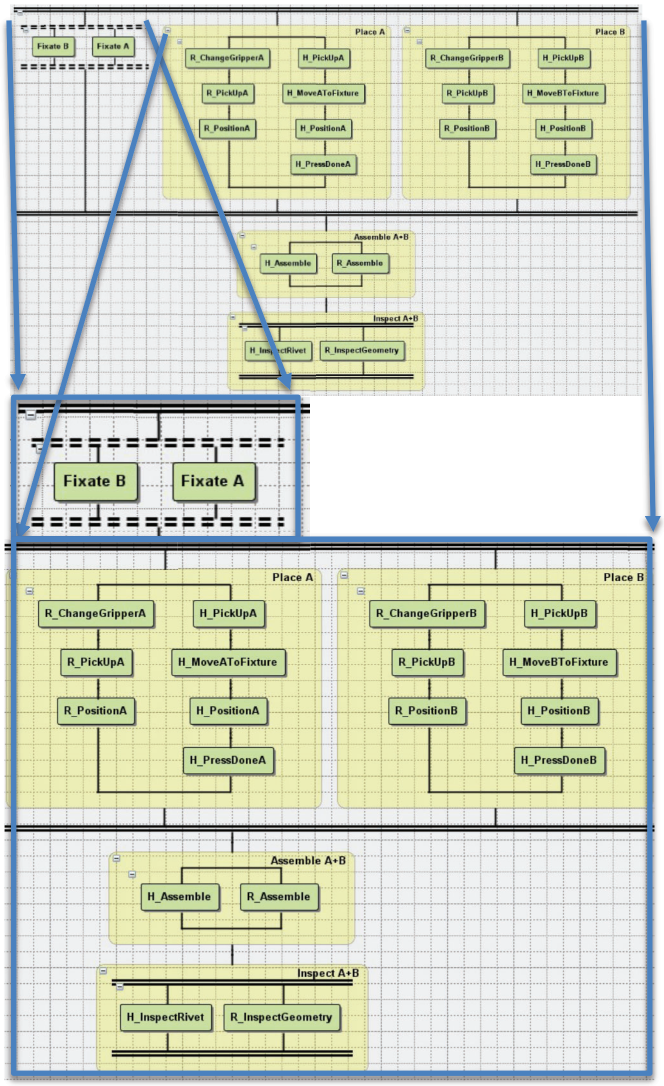

Fig. 4. Task and Resource Allocation using SOP and Competence Matrix (see Table 1)

Both of the *resource allocation* examples try to optimize the "resource allocation" from – an automation-engineering perspective, and uses more technical solutions. In order to get a truly resource allocation, *cognitive task analysis* in necessary. One issue with this is that it relies on subjective and perceived experiences from the operator about skill-based and experiences related to the tasks that is not stored in the IT-system. In order to collect this and to make it accessible, embodied automation can be used. In order to create a resource allocation, there needs need to be a mixture with different analysis and methods, e.g. task analysis, function analysis, cognitive task analysis, and human resource planning. In order to collect the right data from these systems an "automated planning of processes" is vital.

C. Automated Planning of Processes

Computer Aided Process Planning (CAPP) / Computer Aided Manufacturing Planning (CAMP) systems are IT systems that support the reasoning behind the transfer from product features to machine processes [35]. Therefore, despite the name such systems are not in scope of this work. This reminds us in taking care on which level of granularity the term process is used. The work in this paper focuses on processes that run across production systems - including (in particular) workers and robots.

Advanced Planning and Scheduling (APS) systems are concerned with the development of algorithms that focus on processes that run across systems [36].

Already the sub-task of scheduling in these systems is proven to-be "NP-hard" (non-deterministic polynomial-time). This means that for finding the optimal solution of such problems all possible solutions have to be analyzed (non-deterministic). However, already for a few elements that form such problems, the number of solutions to be analyzed exceeds the number of atoms in the universe [37]. Algorithms need polynomial time, because of the increasing number of machine operations needed.

Any automated approach has to cope with that *complexity.* The advantage of using these systems are that the automation of planning allows coping with dynamics. Changes in customer demands, process variants, etc. can be calculated and optimized. However, the "complexity" does not allow finding the global optimum. Only heuristics may be used to search that massive problem space for a solution.

Expert systems are computer systems containing a well-organized body-of-knowledge including facts and if-then rules (also known as production rules) [38]. One example of an expert system shell is CLIPS [39]. A language used to implement reasoning is LISP [40].

A few expert systems have been developed for production planning and control. Benefits reported from expert systems for process planning and scheduling include "more accurate decisions, time gains, improved quality and more efficient use of resources" [41, p. 258]. Expert systems support decision makers in their task. Expert systems are typically programmed with the rules by experts in advanced. Facts, which are combined through rules, are changed to reflect a certain situation. Yet, the system learns through programming and modifications by the human user.

The complexity of the problem, leads researchers to implement distributed systems, which allow encoding different aspects and decentralized reasoning. That, in the simplest case, allows parallel computing. Nevertheless, the overall goal of using distributed artificial intelligence in manufacturing has been to increase flexibility. Partly to meet requirements for small lot size production, partly to increase resilience (i.e. robustness) in production processes [41]. A number of approaches exist, that implement a distributed system for scheduling [41] [42].

In the following, we introduce manufacturing scheduling and control with underlying paradigms of "Multi-Agent Systems" and "Holonic Systems".

One early, well-known holonic systems approach is *PROSA (Product Resource Order Staff Architecture)* [43], which has been extended for automatic planning and scheduling [44]. That system uses a mechanism similar to ants, leaving pheromones that determine the possible production processes in a first step, which is followed by ants leaving pheromones to determine the resource availability and in a third step schedules orders on the shopfloor considering the current situation.

ADACOR² is a distributed manufacturing control and reconfiguration architecture that implements self-organization in holonic multi-agent systems [45]. The overall problem is divided into sub-problems. Every sub-problem is solved taking the level of granularity into account. In *ADACOR²,* each scheduler is composed from a swarm of schedulers. The *ADACOR²* system is capable of self-organizing its structure based on behavior changes of holons. The other way around, the behavior of holons is influenced by the global structure.

Shen et al. [36] provide an overview of such systems, and conclude that a higher degree of interoperability of the multi-agent systems is needed, allowing to place planning and scheduling systems in a wider context.

In [46], an architecture and knowledge management framework based on results of the *KnowRob project* [47], defines data structures for knowledge relevant for assembly processes. This *ontology* includes the configurations of task descriptions, task states and configurations of the robotic system at the workplace – capabilities required/provided by human and artificial agents – involved passive resources, configurations and affordances. The *KnowRob approach* provides the following knowledge-processing features: (a) mechanisms and tools for task representation, (b) automated acquisition of grounded concepts through observation and experience, and (c) reasoning about and managing uncertainty, and fast inference. The knowledge base is implemented in the *Web Ontology Language (OWL). Prolog* is used for loading, accessing and querying ontologies. The ontology captures two levels: (L1) classes that abstract terminological knowledge (type of objects, events and actions – taxonomic fashion) and (L2) instances that represent the actual physical objects and actions that are actually performed [48] [49].

IV. Approach

Based on the above analysis, we conclude that for *human-robot collaboration,* where tasks have to be synchronized, no suitable approach is available that allows to represent complex processes in a useful form and support reasoning and the automated generation of effective processes. That representation and the reasoning should be useable by both, the human and the robot. This is a requirement for meeting the above assumption and allows collaborative robots capable of dynamic sharing of tasks.

A. Model Based Approach

All analyzed approaches above are model-based approaches. There are obvious interfaces to "sub-symbolic artificial intelligence" approaches. *Neuronal networks* may be used for voice-based interaction with the operator. *Deep learning approaches* support engineering intelligent grippers and visual recognition of tasks workers execute.

However, this particular research assumes that meaningful task descriptions are communicated to the agents (semantics), and that robots and humans are capable of executing the 'commands' (pragmatics).

Process models are in the center of this research. *Models* are abstraction of reality, applied in our case to processes. *Workflow-engines* are tools, which support the control flow of processes. Nevertheless, for this work, the *control flow* is only one of multiple aspects. With respect to active resources (i.e. human and artificial agents), the model needs to hold their capabilities, functionality and states. Passive resources (e.g. materials) used for production (like screws) and physical material flows, also need to be represented in the models [8].

B. Human & Artificial Agent Point-of-View

Multiple views are needed in process models. Every process participant has her/his own view. This includes, but is not limited to, tasks that can be executed right now or in the immediate future by a particular agent.

For the execution of a production step, human and artificial agents need to have the capability, the required passive resources and tools to execute that step.

Capabilities may be modelled as roles. *Roles* do specify what can be done by an agent but also specify responsibilities. These can be capabilities to do something or can be capabilities to use some tools to do something.

In this sense, *capabilities* are not static attributes of agents. Also in the simple case where agents enhance their capabilities by getting some additional training.

Passive resources (e.g. screws, paper, etc.) are consumed during the execution of tasks. Passive resource may then enhance the product (screws are found in the product). These may also simply be consumed (and vanish after task execution) like energy for tools.

Following a resource-oriented / agent-oriented approach allows taking two different levels (see also above with S-BPM – III.A). On the one hand, the agent's internal state and behavior. On the other hand, the collaboration or process point-of-view.

This, by design, supports the inclusion of symbolic artificial intelligence approaches and reasoning. It allows designing a multi-agent system where agents have a limited knowledge and collaborate to have intelligence emerge.

Using this agent perspective, it is also possible to use different representations for the individual operators (e.g. at execution, the task-list it is shown to the worker by its intelligent personal assistant – agent). One operator might be represented in the planning system as a newbie, where task execution takes longer than with others. *Process scheduling* gets more realistic by using such possibilities, different roles and role-specific configurations for different performance capabilities.

C. Cognitive Architectures

Models will include rules that are used to construct process models. Such rules include for example pre- / post-conditions and input/output parameters of tasks that can be used to chain multiple processes where output and post-conditions match pre-conditions and input (e.g. materials, information, decisions).

Robots will make use of those representational elements to reason over the processes. They need to be capable to understand what humans do and where tasks need to be synchronized. This is of importance, as the human agents are "no-static models", but the executed behavior is dependent on the capabilities of the worker executing a particular role.

Cognitive architectures have been researched, to allow the artificial agent in general, the robot in particular, to reason (in a human like fashion) over processes [49]. Such cognitive architectures (e.g. SOAR) allow robots not only to reason using pre-existing rules, but also learn about processes in general and the execution of certain tasks by different operators in particular.

Agents are used to represent concrete workers for the planning processes. This representation should consider the current skill-level in order to have a realistic plan with process times dependent on the worker's capability and speed. The "agent paradigm" allows bringing in the personal view of operators on certain tasks.

V. Conclusions

In this initial work, we focused on the analysis of the existing elements to be used to build a system that allows constructing processes where human and robots collaborate. Particular attention should be given to the operator point-of-view. This is partly possible due to the *agent-based approach,* partly because we are also seeking to involve robotics solutions that have the capabilities of human-like reasoning (i.e. cognitive capabilities). The agent-based approach provides by design the desired and reality-reflecting structure of the production systems.

Agents represent humans or robots and have a long-term memory of their state. Different roles might be taken by agents to execute sub-processes according to the role. The role will be assigned "dynamically" and might "change over time" for a particular task, this in order to implement learning and continuous improvement.

In its current state, this work provides the ground for a new system that supports the Operator 4.0 in large and complex production processes. The current preliminary state of this research project does not allow reporting on details. However, we have identified several objectives on which we will work in the near future.

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