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Procedia CIRP 52 (2016) 1 – 5

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Changeable, Agile, Reconfigurable & Virtual Production

Determinants of an appropriate degree of autonomy in a cyber-physical production system

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Abstract

Classical productions systems are migrating step-by-step into cyber-physical production systems. The addition of much more computing power and object-bound data storage will lead to new possibilities for the advancement of autonomy in production systems. Autonomous message exchange and coordination can help to prevent quality problems (for instance wrong pairing of tool and work piece) and improve the disturbance management (for instance by faster information about current and probable disturbances). Due to the fact that nearly all improvements of existing production systems with cyber-physical systems take place in real and active manufacturing sites, on-site experiments for determining an appropriate degree of autonomy for production objects are not feasible. Therefore, a lab approach is necessary. In this contribution a hybrid lab approach to simulate various degrees of autonomy is presented [1]. The paper starts with a definition of autonomy and suggests diverse measurement methods [2]. After a short introduction into the lab concept, the results of some test runs are presented where autonomous objects perform the same production program as "dumb" production objects. Finally, an outlook for further research is given.

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016

Keywords: Autonomy, Cyber-Physical Systems, Hybrid Lab Approach, Production Process Characteristics

1. Autonomy and ways to measure it

There are different ways to describe and measure autonomy in cyber-physical production systems (CPPS). Basically, autonomy is defined as the ability of an entity to structure its own action and environment independently and without unwanted influence from the outside. Measuring protocols only exist in medicine and psychology nowadays. In Artificial Intelligence autonomous agents are not dependent from the goals of other entities [3]. Agent autonomy means that agents have control over both their internal state and over their behavior [4].

Therefore new definitions of autonomy are useful that can be applied on production systems. In this contribution two approaches to define the autonomy of a production system are presented: a descriptive approach and an approach which is based on the simulation of entity behavior in a market model. Autonomy is adjustable, following van der Vecht [4], when the agent is able to choose a distinctive style of decision-making and of coping in an agent organization. There are several ways to achieve coordination within an agent organization. Approaches range from emergent coordination, where the actors are autonomous and the coordination is implicitly implemented, to explicit coordination, such as a hierarchical organization where the actors have no decision autonomy, but solely follow the orders from their superiors.

In the context of logistics processes, the following definition of autonomy was given [5]: Autonomous control describes processes of decentralized decision-making in heterarchical structures. It presumes interacting elements in non-deterministic systems, which possess the capability and possibility to render decisions independently. The objective of Autonomous control is the achievement of increased robustness and positive emergence of the total system due to distributed and flexible coping with dynamics and complexity. During the last years, the importance of autonomy in production systems increased fundamentally. One core capability for Industry 4.0 (a term mainly used in

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016
doi:10.1016/j.procir.2016.07.063

Germany) or Smart Production [6] are autonomous production objects like (semi-finished) products, machines, tools or transportation which are able to proceed information and make and execute decisions on their own [7].

This paper names two approaches to determine the right degree of autonomy, following the characteristics of a given production process. The research on agents cannot be transferred fully to production systems due to the fact that production systems consist of by design designated elements (agents) with (1) no degree of autonomy, with (2) some extent of autonomy and (3) with a high degree of autonomy. Therefore, there cannot be a unified determination of the optimal degree of autonomy but a specific determination of the degree with different results for diverse production systems instantiations.

Table 1: Classification of manufacturing systems [8]

Attribute	Attribute values			
Product range	Specification by customer	Serial products with customer-specific variations	Standard products with variations	Standard products without variations
Product structure	One-piece-product	Multiple-piece-products with simple structure	Multiple-piece-products with complex structure	
Order trigger	Manufacturing on demand with single orders	Manufacturing on demand with blanket orders	Manufacturing on stock	
Disposition	Following the customer's order	Mainly following the customer's order	Mainly MRP-based	MRP-based
Demand planning	No relevant external supply	Relevant external supply	Huge external supply	
Manu-facturing process	Unique manufacturing	Unique and small lot manufacturing	Serial manu-facturing	Mass manu-facturing
Manu-facturing organization	Construction site	Shop floor	Group-/ line assembly	Line production
Share of self-manufactured parts	Low	Medium	High	

To be able to differentiate between production systems, a classification system stemming from Schomburg [8] is used (Tab 1). The model to determine the right degree of autonomy is depicted in Fig. 1. Based on similar concepts to adjust the degree of adaptability in turbulent environments [9,10,11], there might be a discrepancy between the necessary amount of autonomy in a certain environment and the actual degree of autonomy.

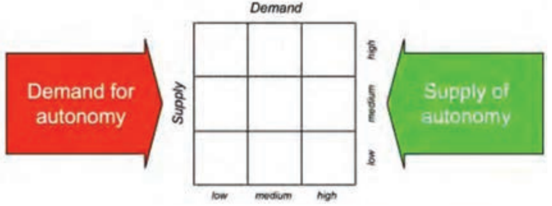

Fig. 1. Model to compare demand and supply of autonomy.

The optimal degree of autonomy can be calculated by comparison of the least necessary degree of autonomy with the actual deliverable degree of autonomy. The actual deliverable degree of autonomy can be calculated using one of the approaches briefly described below, the descriptive approach and the market-based approach. After a short explanation of the two approaches, the necessary degree of autonomy is derived from manufacturing characteristics in Tab. 1.

1.1. Descriptive approach

The core element of the descriptive approach is the Autonomy Index (AI) that puts into relation the autonomous parts of a considered value stream to the entire value stream. The calculation of AI [12] is briefly described in the following subsection.

The Autonomy Index [2] specifies the degree of autonomy used in the production process. The term was chosen following the term Lean Index used in Toyota‘s Value Stream Design [13]. While defining the index, the basis for the comparison had to be determined. There are various possibilities, e. g.:

- Number of autonomous processes: number of all processes
- Number of autonomous process steps: number of all process steps
- Autonomous controlled process time: total cycle time
- Autonomous quantity of data: total quantity of data

The practical execution has shown that the number of autonomous process steps is the most suitable of the above-mentioned possibilities. Relevant data can be accorded in a laboratory and even on site in the shop floor without extensive time- and cost-consuming experimental procedures. Autonomy in production systems cannot solely be achieved by hardware autonomy but also by autonomy of humans and software [13]. These three enablers – also called levels – of autonomy can be considered by means of the Autonomy Index. Furthermore, two additional key figures were defined to characterize the autonomous system more detailed: the Interaction Index II and the Communication Index CI. The Interaction Index II describes the proportion of autonomous process steps executed with the aid of communication of actors within the same level to the total amount of process steps in this level.

The Communication Index CI roughly describes the proportion of autonomous process steps executed with the aid of communication of actors of the same level to actors of another level to the total amount of process steps that are executed in this level with the aid of communication to actors in another level.

The Autonomy Index AI describes the proportion of autonomous process steps to the total amount of process steps.

1.2. Autonomy as the result of acting on markets

The market approach [14] relies on the following abstract understanding of a CPS’s degree of autonomy (DoA): The CPS acts autonomously if it decides completely self-determined (DoA = 100, autonomy). If the decisions of a CPS are solely determined by others, its autonomy is zero (DoA=0, heteronomy). The CPSs are interpreted as participants of a cyber-physical market (which is represented in the CPPS) on which each individual CPS interplays with its environment. The similarity to real market mechanisms can be used to find the optimal setting for each production component and optimization dimension.

The market autonomy model is built up on the following assumptions:

Assumption 1: Any CPS communicates with any CPS such that a fully meshed communication structure exists.

Each CPS as a market player is able to overview the market. No market anomalies with regard to information deficits distort the ideal market model.

Assumption 2: The determination of the CPS specific optimum is based on the interplay of the individual CPS and its environment, which can be seen as market equilibrium.

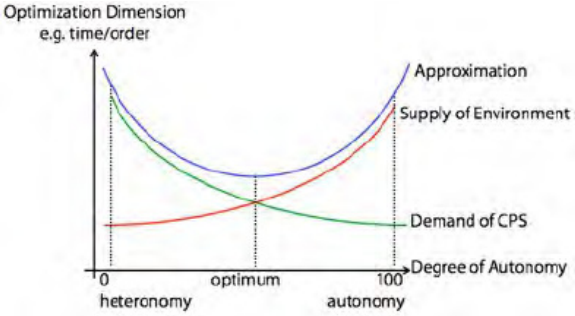

Fig. 2. Supply and demand of each CPS.

In Fig. 2, this equilibrium can be seen at the intersection of the red and green curve. Those curves are described in the following.

The green curve shows the demand of a single CPS. For example, this could be a work piece that is in the search for a coloring machine. It intends to minimize its general time per order. The more self-directed it can select the required offer combination to be colored given by its environment, the smaller will be its time per order. The more other-directed those offers are selected by the environment, the greater will be the CPS’s time per order. This is because further CPSs have to be considered as well and they may be preferred.

Of course, the curves of the individual CPS‘s can be consolidated as well. Imagine, we have several CPSs as consumers of production services, so their individual demand curves can be added to a cyber-physical market demand curve. Equally, the cyber-physical market supply curve can be created based on the supplies of further CPSs (see red curve in Fig. 2).

The equilibrium can be found at the intersection of the red and green curve. It is referred to a pareto optimal degree of autonomy and describes the situation where no possibility to improve the situation of an individual CPS exists without worsening the situation of another CPS.

Assumption 3: The single CPSs as demanders and suppliers consider the prices of their optimization dimension as given.

This means, that the CPSs do not recognize their actions to influence the prices and they try to realize the best possible actions for a given market price. This situation can be interpreted as a competitive market.

Assumption 4: The elasticity of the supply decreases by increasing the degree of autonomy and the elasticity of the demand increases by increasing the degree of autonomy.

For the supply of the environment, small degrees of autonomy are characteristic to have lower values with regard to the optimization dimension than greater degrees do have. On the demand side of the CPS it is vice versa.

From the perspective of a machine, these curves can be interpreted as follows: The green curve shows the demand of a single coloring machine that is in search for CPSs to be colored. It intends to minimize the time per order. The more self-directed it is able to select the required offer combination given by its environment, the smaller will be its time per order. The more other-directed those offers are selected by the environment, the greater will be the CPS’s time per order. This is because of the influence of other CPSs, which can be preferred as well.

The red curve stands for the market supply curve and represents the specific offers of the machine’s environment. More self-determined selections do show higher times per order since the fulfillment of more CPS specific needs to come along with the disregard of others. More other-directed selections do show lower values of the optimization criteria because the solution was found centrally and no specific needs had to be considered. Again, the pareto optimal degree of autonomy can be found at the intersection of those two curves since the specific and system wide perspectives are considered. Here, the CPPS is not dependent on the evaluation criteria of only one system and the strengths of a harmonic CPPS can be realized efficiently.

Assumption 5: The demand and supply curves can be approximated with the help of a squared curve. Based on this assumption, only three points are needed to specify the approximated curve.

Since those optimization curves are expected to be influenced by the elements of a CPS, further assumptions have to be formulated with regard to the CPS itself. This includes assumptions about the processor(s), sensor(s), communicator(s) and the actuator(s), as well as its environment, based on disturbances (e.g. machine erosion, work piece defects, human motivation, conveyor bottlenecks, loading equipment lost, etc.) and enhancements (e.g. machine processor speed up, work piece sensor updates, human qualification, conveyor technique innovations, loading equipment shape optimization, etc.).

1.3. Demand side

On the demand side there might be a calculation of the necessary amount of autonomy using a formula, where a high coordination effort and a dynamic variance of requirements during manufacturing lead to a higher amount of autonomy, while no need for coordination and strictly predictive requirements lead to a very low demand for autonomy.

In Tab. 2 a rough calculation of the necessary amount of autonomy is provided using the example of a medical technology company manufacturing artificial knee joints.

Table 2. Example for the calculation of needed autonomy.

Attribute	Attribute values				Actual	Max
Product range	Specification by customer	Serial products with customer-specific variations	Standard products with variations	Standard products without variations		
Need for autonomy	++	+	o	-	0,33	1
Product structure	One-piece-product	Multiple-piece-products with simple structure	Multiple-piece-products with complex structure			
Need for autonomy	-	o	+		0,33	1
Order trigger	Manufacturing on demand with single orders	Manufacturing on demand with blanket orders	Manufacturing on stock			
Need for autonomy	++	+	o		0,66	1
Dispo-sition	Following the customer's order	Mainly following the customer's order	Mainly MRP-based	MRP-based		
Need for autonomy	++	+	o	-	0,33	1
Demand planning	No relevant external supply	Relevant external supply	Huge external supply			
Need for autonomy	o	+	++		0,66	1
Manufacturing process	Unique manufacturing	Unique and small lot manufacturing	Serial manu-facturing	Mass manu-facturing		
Need for autonomy	++	+	o	-	0,33	1
Manu-facturing organi-zation	Construction site	Shop floor	Group-/ line assembly	Line production		
Need for autonomy	+	++	+	-	0,66	1
Share of self-manu-factured parts	Low	Medium	High			
Need for autonomy	o	+	++		0,66	1

2. Validation lab approach

The simulation environment [15, 16] consists of a composition of physical and computer based models. The main components are the work pieces and the machine tool demonstrators as well as transport lines which connect the various machine tool demonstrators. The demonstrators with their ability to communicate in different ways and the flexible transport system provide an effortless integration of hardware components into the overall system. The software is designed for a quick integration of sensors and other devices using standard communication protocols such as OPC UA. The hardware section provides the interfaces for an easy connection and integration of new hardware.

The simulation environment is both, software architecture and a hardware platform. The system supports the integration of hardware-components by design. This is an important advantage compared with pure software models, which are supplemented by some hardware parts. For an investigation of receiving characteristics in a RFID-scenario, for example, it is not sufficient to connect merely a reader device, but in addition it is necessary to realize moved work pieces with a kind of conveyer. A cost intensive construction of further hardware parts is imperative for good results. Thus, the presented approach avoids these efforts. Figure 3 shows samples of the hybrid simulation environment. The left picture displays a work piece or work piece carrier. The right picture shows a load procedure of a machine. In the foreground a conveyor is seen.

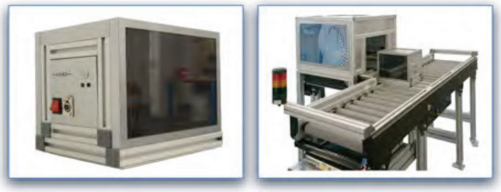

Fig. 3. Components of the hybrid simulation environment [1].

3. Results from first experiments

In a first experiment using the lab approach described above, the communication-based definition of autonomy was used to compare a fully autonomously acting work piece (“smart work piece“) against a strictly central controlled (“dumb“) work piece. Both work pieces (artificial knee joints) went through the same manufacturing process simultaneously. The logistic infrastructure was set to respond to commands of the smart work piece and of the central dispatcher for the dumb work piece. For this first experiment no disturbances were implemented. The whole communication between the components in the factory was logged and afterwards analysed. The experiment was repeated 70 times to get proper values for the communication between the factory components.

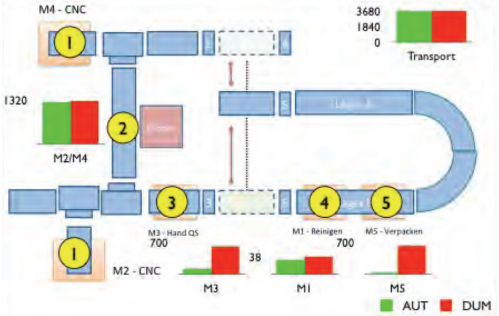

Fig. 4. Results from a comparative run between “dumb” (DUM) and “smart” (AUT) work pieces.

The results are shown in Fig. 4. Due to the fact that transport tasks are real and therefore equal for both work pieces, differences can only occur when a work piece is waiting for processing. In Fig. 4 one can see the different amounts of time needed for processing stations M3 and M5. The “smart“ work piece is typically faster there. This can be explained with additional waiting time for the “dumb” work piece in front of the unit, while the “smart” work piece only moves when it is guaranteed that it will be processed immediately after arrival. When pieces of equipment are available twice, there is only a very short difference in processing time, because no waiting time occurs (in this scenario).

Tab. 3 shows some key figures collected during the experiment.

Table 3. Key figures from the autonomy experiment.

Property	Autonomous work piece	Centrally controlled work piece
Autonomy Index AI	1 : 1,5	1:∞
# „waiting for worker“ (per order)	0	5
# Information exchange with central control (per order)	54	980

4. Outlook and further research

Based on the research approach described above, the following tasks will be realized in the future:

The dimensions of autonomy, optimization and influencing factors (processors, sensors, communicators, actuators, disturbances and enhancements) have to be developed. Additionally, assumptions for those dimensions have to be formulated as well.

The modeling and its underlying assumptions have to be verified by the aid of real systems or simulation systems like the lab environment described above.

Test runs of a cooperative planning approach based on different CPS decision strategies and combinations of them have to be realized such that its effects on the optimal degree of autonomy becomes transparent.

A simulation software has to be build, which fits to the real test run results and can be used to realize fast and cheap simulated test runs.

Probably there still exist several optimal areas when further factors will be considered. Hence, this means that the transformation of traditional production systems to the optimal CPPS is dependent on the specific situation of a production setting, which underlines the importance of a systematic approach and the necessity of real test runs.

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