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A classification pattern for autonomous control methods in logistics

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Abstract Autonomous control in logistics enables single logistics objects to control the production and transportation process. This shift from central planning to decentralized control in real-time offers many possibilities to cope with highly dynamic and complex systems. The algorithms that define the decision behavior of each logistics object, autonomous control methods, play a key role in the successful implementation of autonomous control in logistics systems. A transparent classification is needed in order to identify the basic elements these methods consist of. This classification supports the evaluation of autonomous control methods in terms of gaining knowledge about which method characteristics are responsible for a method's performance. This paper defines what autonomous control methods are, works out their fundamental characteristics, presents multiple methods developed so far, and compares these methods regarding characteristics and performance.

Keywords Autonomous control · Categorization · Decentral · Logistics · Production planning and control

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1 Introduction

In the past few years, a change can be observed in the area of logistics. Technological developments and changing market conditions have resulted in rising complexity in production and consequently in logistics. These changes include an increasing number of product variants, faster delivery times, and shorter product life cycles [7]. The complexity of nowadays logistics processes has significant impact on the performance of logistics processes in terms of delivery time and delivery reliability [3, 5, 8, 18]. A new approach to deal with complexity is to increase the level of autonomous control in logistics processes [10]. The Collaborative Research Center (CRC 637) "Autonomous Cooperating Logistic Processes—A Paradigm Shift and its Limitations" in Bremen, Germany, aims at developing new methods in production planning and control (e.g. [12, 13, 17]) as well as in transportation control (e.g., [9, 15]) in order to overcome the obstacles created by today's complexity and dynamics. Simulation studies have already shown that increasing the level of autonomous control improves the logistic performance [14]. At the same time, the availability of new information technologies such as any type of wireless communication (e.g. RFID), distributed computing, and computer miniaturization serves as an enabler for autonomous control. The CRC focuses its work on decentralized methods that have the ability to utilize given flexibility potentials in logistics processes [23], but also on gaining more knowledge on autonomously controlled system behavior, e.g. identifying the limitations of autonomous control.

Several different autonomous control methods have been developed and tested in simulation studies. These previously conducted studies have illustrated that autonomous control can realize a higher logistics target achievement in comparison to conventional production planning and control [9, 14, 25]. However, it remains unclear which basic characteristics make up autonomous control and what is their influence on the logistics system performance. The goal of this work is to identify basic elements of autonomous control methods and their influence on performance so that future methods can be developed systematically by focusing on parameters that contribute to a higher achievement of logistics targets.

This paper provides an overview on the current understanding of autonomous control in logistics as well as, more specific, on the term *autonomous control methods* in Sect. 2. By collecting the basic elements of these methods, a classification pattern is elaborated. In Sect. 3, a literature survey of currently available autonomous control methods is presented. The methods are classified in terms of the previously developed pattern, and a systematic similarity analysis is conducted. Section 4 presents a comparison of the methods' performance. The performance evaluation has been done using computer simulations. The conclusion brings together all insights and points out the next steps for research in this field.

2 Autonomous control methods

For getting a better understanding how autonomous control works if applied in manufacturing and transportation environments or in computer simulations for scientific purposes, it is necessary to consider the single elements that compose an autonomous controlled system. Autonomous control itself is defined as follows:

> "Autonomous control in logistics systems is characterized by the ability of logistics objects to process information, to render and to execute decisions on their own." [24]

The definition consists of different elements from different layers. On the one hand, there are the logistics system, the logistics objects, and the information, which are structural elements that describe the environment in which autonomous control takes place. Information processing and decision rendering and execution on the other hand are activities that characterize the way the flow of goods is controlled in such a system. Thus, two different layers can be observed in a logistics system: the logistics processes as well as the control methods that operate on the logistics processes. In this paper, the focus is set on control methods that enable logistics objects to take their own decision in contrast to a scheduled and centralized production planning and control strategy.

A prerequisite for the survey presented in Sect. 3 is having a definition of the term autonomous control method as well as a scheme for characterization. From the above mentioned description of autonomous control and its elements follows this definition:

> An autonomous control method is a generic algorithm that describes how logistics objects render and execute decisions by their own.

There are many different ways an autonomous control method can operate. A simple method could allow each semi-finished part to choose the next production step in a job-shop scenario by preferring that machine with the lowest number of waiting items in front of a machine [11]. Another example is a method that is inspired by ants' foraging behavior. It uses virtual pheromones, emitted by the parts, which then indicate a preferred path through the production [4]. The diversity of possible autonomous control methods leads to the questions of the methods' individual performance and calls for a comparison of these methods. A previously developed *Autonomous Control Application Matrix* is available to support the evaluation and comparison efforts [22]. A comparison of simulation results is presented in Scholz-Reiter et al. [14], but only taking into consideration three different methods and aiming at showing the relation between process complexity and level of autonomous control. Beside the evaluation of single methods, it is necessary to understand the structure of a method and to be able to identify similarities and differences in order to interpret the comparison results. Additionally, the categorization presented in this paper can be used in the future to create a toolbox for autonomous control method development. Upon availability of performance results for multiple methods, the performance can be connected to the method characteristics and thus offers information which characteristics to consider when creating a method for a specific application purpose.

A recent approach for classifying autonomous control is called the Catalogue of Criteria for Autonomous Control in Logistics [2]. This catalog collects criteria from the decision-making, information processing, and decision execution. For each criterion, four possible properties are offered for classifying the logistics system. The result of the classification leads to a degree of autonomous control. This degree describes—taking into consideration the thirteen different criteria—how much a system is autonomously controlled and thus makes different logistics systems comparable in terms of the usage of autonomous control. For the purpose presented in this paper, namely making the building blocks of autonomous control methods visible, this approach is not feasible as it only offers the degree of autonomous control as a single figure but is not able to compare multiple methods regarding their basic elements of their construction.

Coming from the methods that have been analyzed, characterization of autonomous control methods can be done by using seven dimensions that have been defined: temporal data, planning steps, artificial values, communication type, data scope, actor, and data storage. Each dimension is separated in reasonable sections, e.g. planning steps can be described in discrete steps as 1, 2, 3, or more planning steps. For categorization purposes, the dimension values have been arranged in up to four groups. An overview of dimensions, values, and descriptions can be found in Table 1.

The dimension *Temporal data* indicates whether the method uses data from the past, future, or both. Past data are defined as any kind of figure that can be extracted from the environment, e.g. buffer inventory level of a machine, moving average of processing time at a machine, etc. Future data can be planned data or estimated values for the above mentioned figures. Caution should be exercised at this point as estimated values are often determined by calculating averages from past data, and thus, these kind of values have to be classified as past data. The number of *Planning steps* points out how deep the algorithm searches in a decision tree. Usually autonomous control methods are kept simple and have a very short information horizon, which corresponds to having 1 planning step, but some algorithms additionally take into consideration what can happen two, three, or more steps after the pending decision. *Artificial values* are figures that are not extracted directly from the environment but are generated by the algorithm itself. These artificial values can be pheromones as presented in the above mentioned ant approach, but also virtual money used in auction-theoretic approaches. The *Communication type* describes how communication is conducted by the algorithm. It distinguishes between communication among the moving logistics objects (parts), among the fixed objects (machines), among all objects, or communication with a central control entity. The communication itself can range from a simple data request (e.g. a part demands the current buffer inventory level from a machine) to extensive negotiations between agents (e.g. parts bidding in an auction for resources). The *Data scope* provides information about the number of variables used for decision making. The dimension *Actor* points out whether the parts, the machines, or a central entity act as decision maker in the algorithm. An issue regarding this dimension is the fact that from the decision point of view, it is not important who takes the decision. Only the input parameters and the target system define the outcome of the decision. This dimension is nevertheless part of the categorization, as it plays an important role when implementing an autonomous control method in a real logistics environment. The hardware layout of an autonomous control solution is strongly influenced by this characteristic. Finally, *Data storage* describes where the figures are stored that form the basis for decision making. Again, this dimension is closely related to the hardware implementation.

Table 1 Autonomous control categorization dimensions

Dimension	Values	Description
Temporal data	Past Future Hybrid	Indicates whether the method uses data from the past, future (planned), or both
Planning steps	1 2 3 More	Number of future steps (e.g. machines) the method considers
Artificial values	No Static Dynamic	Usage of artificial values for decision making, e.g. virtual pheromones
Communication type	Part-machine Part–part Machine–machine Central	Communication and data exchange between logistics objects or a central entity and logistics objects
Data scope	Low (1–2) Medium (3–5) High (>5)	Number of variables used for decision making
Actor	Part Machine Central	Logistics object that actively decides
Data storage	Part Machine Central	Location of data storage

3 Autonomous control methods survey

In this section, autonomous control methods presented in the literature are described, characterized in accordance with the above defined dimensions, and compared by performing a systematic similarity analysis.

3.1 Methods description

Various methods for autonomous control in logistics are available today. Some of them have been developed in the course of the research of the CRC 637, while others were invented without explicitly naming them autonomous control methods. The descriptions of each single autonomous control method identified can be found in Table 2.

Table 2 Autonomous control methods survey including method name (short name in parentheses), key idea, basic algorithm description, and remarks

Method	Ant algorithm (Ant)	Cunning ant system (C-Ant)
Source	Ant colony control for autonomous decentralized shop floor routing by Cicirello and Smith [4]	The cunning ant system by Tsutsui and Pelikan [16]
Key ideas	Ants carry products	Two different types of ants exist
	Different jobs have different types of pheromones	c-Ants, cunning Ants base most of their path on previous paths
	Machines have pheromone concentrations	d-Ants are conventional ants, who donate their path to the c-Ants
	Ants choose machines based on pheromone concentration	Both locate pheromones at spots on their path
	Pheromones expire over time	different pheromones will be overwritten
	Optional: ants sometimes choose machines randomly	pheromones evaporate after some time
Algorithm	1. Initially choose a random machine	1. Let in some d-ants and some c-ants
	2. Avoid machines with different pheromones	2. Let the d-ants choose the paths with the higher pheromone concentration with a higher likelihood
	3. Go to machines with same pheromones	3. Let already deposited pheromones expire at a constant rate
	4. Let pheromones expire after some time	4. Let c-ants retrieve the paths of the d-ants and use them partially for their own paths
	5. Increase pheromone concentration if ant has visited the machine	
	6. Overwrite old pheromones if the pheromone type of the ant is different	
	7. Update pheromone concentrations once ant is through	
	8. Optional: choose a random machine	
Remarks	Long initiation time; Not flexible if job influx changes	Algorithm avoids stagnations and is thus more flexible than the ordinary ant algorithm

Method	Pheromone approach (Ph)	Bee foraging (Bee)
Source	Autonomous control of production networks using a pheromone approach by Armbruster et al. [1]	Autonomous control of a shopfloor based on bee's foraging behaviour by Scholz-Reiter et al. [13]
Key ideas	Average throughput time is used as a pheromone	Bees indicate good food sources via dancing
	To model evaporation, only the last n throughout times are considered	Food sources are measured by quality and quantity
	Number of relevant parts for the throughput time is the rate of evaporation	More bees go to the better sources
Algorithm	1. Calculate average throughput times for the last n parts	1. Choose the best food place
	2. Go for the machines with the lowest average throughput times	2. Different food sources (machines) exist
		a. Advertise (dance) and send information
		aa. Number of recruited bees depends on the number of dances
		ab. The quality of the source depends on the length of the dance
		b. Just use but don't recruit
		c. Abandon machine and join pool of unemployed bees
Remarks	Slow adjustment to change	Long initiation time
		Not flexible if job influx changes

Method	Simple rule based 1 (SRB 1)	Simple rule based 2 (SRB 2)
Source	Autonomous control of a shop floor based on bee's foraging behaviour by Scholz-Reiter et al. [13]	The Influence of Production Networks' Complexity on the Performance of Autonomous Control Methods by Scholz-Reiter et al. [11]
Key ideas	Compares estimated waiting time at buffers	Compares estimated waiting time at buffers
	Uses future events	Uses data from past events
Algorithm	1. Parts are rated in estimated processing time	1. When a part leaves a machine it sends information about the processing times

Table 2 continued

Method	Simple rule based 1 (SRB 1)	Simple rule based 2 (SRB 2)
	2. Current buffer levels are calculated as a sum of the estimated processing time	2. This information is used by the following parts to decide where to go next
	3. Choose the machine with the lowest processing time buffer	3. Parts choose the machine which provides the lowest mean duration of waiting and processing for parts of the same type
Remarks	Useful with high number of machines	Useful with high number of products; Changes more slowly compared to the previous method

Method	Queue length estimator (QLE)	Due date (DD)
Source	Modeling and analysis of production logistics processes based on biologically inspired strategies by J. Bendul (Master's thesis, University of Bremen, Germany)	Modeling and analysis of production logistics processes based on biologically inspired strategies by J. Bendul (Master's thesis, University of Bremen, Germany)
Key ideas	Computes and estimates buffer states	Uses the queue length estimator (QLE)
	Part decides autonomously based on various factors	Orders parts by earliest due date
Algorithm	1. All buffer states of machines that can perform the next step are computed	1. After a part leaves a machine it chooses its next destination based on the QLE method
	2. The part decides whether to switch to a different production line based on processing times or setup times, using local information	2. Within the queue of parts to be processed the part with the most urgent due date is chosen to be processed next
	3. Parts compare their own estimated time with the estimated time of the parts in the buffers and takes the machine with the minimal time	
Remarks	Similar to the simple rule methods above	Similar to the simple rule methods above

Method	One logistics target per rule (OLTPR)	Market based control (market)
Source	Developed in this research group	Developed in this research group according to Vollmer [20]
Key ideas	Implement various rules at the machines and parts, where each rule tried to achieve a specific logistics target	Virtual currency is introduced
	Can be easily extended with new rules to further improve outcome	Parts carry a shopping list of work that needs to be done on them
		Each job needed for a part has a budget associated
		Distance traveled to the machine has a price
		Parts auction for access to the machine
		Shopping List can be altered during the production process
Algorithm	1. Utilization: each machine send a stronger attraction signal as its buffer becomes less full	1. Parts with shopping list and budgets enter the production process
	2. On time delivery: parts are prioritized by their due date	2. Parts bid on the machines on their shopping list
	3. On time delivery: parts prefer machines with short throughput time	3. Highest bidder gets access to the machine
		4. The parts bid according to the minimal price of the machine and the distance cost
		5. Machines grant access for the parts, if they are the highest bidder
Remarks	The various rules have to be weighted appropriately to achieve good performance	It is not clear how to choose the budgets
		Price levels on the machines are important for production activity
		Development of price levels might be usable to investigate overall state of the production process, thus provide macro data
		Production is more dynamic as shopping lists can be altered during the process

Table 2 continued

Method	Holonic manufacturing (Holonic)	Bionic manufacturing system (Bio)
Source	According to van Brussel [19]; A market approach to holonic manufacturing by Markus et al. [6]	Reinforcement learning approaches to Biological Manufacturing Systems by Ueda [17]
Key ideas	Two agents bargain over the next item to be processed	Attraction fields dependent on the type of job exist
	Agents are machines and management	Fields attract specific jobs
	Management and machines bargain for the jobs to do	Jobs have DNA like information about what work needs to be done on them
	Management punishes machines for delays	Machine have operating knowledge that evolves
	Machines bid to get jobs from management	
Algorithm	1. After a part leaves a machine it chooses its next destination based on the QLE method	1. Machines(Robots) are attracted by fields
	2. Within the queue of parts to be processed the part with the most urgent due date is chosen to be processed next	2. Parts send out fields, depending on the production process they require
Remarks	Punishment have to be chosen carefully	No specific algorithm provided
	Existence of social dilemma; machine decision might cause overall loss, but gain for machine	Based on manufacturing processes that require robots and on the spot machines
	Requires a central authority	

Method	Link-state internet routing protocol (LSIRP)	DLRP (DLRP)
Source	Developed in this research group according to Wenning et al. [21]	Autonomous control by Means of Distributed Routing by Wenning et al. [21]
Key ideas	Based on a link-state routing protocol	Parts request a route from machines
	Each machine has a map of the entire facility	Machines communicate best routes to a destination
	Parts can be sorted according to any rule	
Algorithm	1. A map of the facility and the connections between machines is built/provided	1. Each machine is a knowledge broker
	2. Shortest paths are computed based on various chosen criteria, generally using Dijkstra's algorithm	2. Before a part decides on a best route it ask the current machine about possible ways to reach the destination
	3. As the situation changes (breakdowns, buffer states, new machines) only the changes are propagated among the machines	3. Each machine includes relevant information from its knowledge base and forwards it to its successors
	4. To make sure that insignificant changes are not propagated there must be a lower threshold	4. The successors do the same and forward this information along the production chain
		5. The request is propagated through the network until the destination (drain) is reached
		6. Then the last broker (the drain or the last machine) sends a reply directly to the part with all the collected information
		7. After receiving one or multiple probable paths the part decides on the better way to take
Remarks	The machines can self-organize if information about the part production cycle is included	A timeout may be included to reduce the amount of waiting for possible paths
	The threshold may need to be scaled by the local buffer level	Can be computationally expensive

3.2 Systematic comparison of autonomous control methods

A systematic comparison of two autonomous control methods can be achieved by a mathematical definition of the similarity between two methods. For two autonomous control methods M^k and M^l, the similarity is labeled S^{kl}. Similarities can be defined for each categorization dimension, and the similarity for the i-th categorization dimension is labeled S_i^{kl}. The total similarity S^{kl} between two autonomous control methods M^k and M^l is defined as the arithmetic mean of the categorization-based similarities $S_i^{kl}: S^{kl} = \frac{1}{n}\sum_{i=1}^{n} S_i^{kl}$. The categorization-based similarities S_i^{kl} are defined for each categorization dimension individually.

The similarity S_1^{kl} for temporal data is given by the following similarity matrix:

$$\begin{array}{cccc} & \text{Past} & \text{Hybrid} & \text{Future} \\ \text{Past} & 1.0 & 0.5 & 0.0 \\ \text{Hybrid} & & 1.0 & 0.5 \\ \text{Future} & & & 1.0 \end{array} \quad (1)$$

According to this definition, two methods are completely similar with respect to the temporal data if they use data from the same temporal range. Distinctions about the data number, origin, and quality are not made in the present analysis.

The similarity S_2^{kl} for planning steps is defined by a 4 $\times$ 4 similarity matrix:

$$\begin{array}{ccccc} & (1) & (2) & (3) & (>3) \\ (1) & 1.0 & 0.5 & 0.333 & 0.0 \\ (2) & & 1.0 & 0.5 & 0.0 \\ (3) & & & 1.0 & 0.333 \\ (>3) & & & & 1.0 \end{array} \quad (2)$$

The present analysis does not make a distinction for methods using more than 3 planning steps.

The similarity S_3^{kl} for artificial values is defined by the following similarity matrix:

$$\begin{array}{cccc} & \text{No} & \text{Static} & \text{Dynamic} \\ \text{No} & 1.0 & 0.0 & 0.0 \\ \text{Static} & & 1.0 & 0.5 \\ \text{Dynamic} & & & 1.0 \end{array} \quad (3)$$

Autonomous control methods using artificial values have no similarity to methods using no artificial values. Autonomous control methods using static artificial values are defined as 50% similar to methods using dynamic artificial values.

For the communication type, the four values are nonexclusive, and more than one communication type can be realized in an autonomous control method. The similarity S_4^{kl} for the communication type is defined as the arithmetic mean of the similarities for all communication types:

$$S_4^{kl} = \frac{1}{4}\sum_{j=1}^{4} S_{4j}^{kl} \quad \text{with} \quad S_{4j}^{kl} = \begin{cases} 1: & M_{4j}^k = M_{4j}^l \\ 0: & M_{4j}^k \neq M_{4j}^l \end{cases} \quad (4)$$

The similarity S_5^{kl} for data scope is defined by the same similarity matrix as S_1^{kl} with the labels replaced by low, medium, and high.

The similarities S_6^{kl} and S_7^{kl} for actor and data storage, respectively, follow the as definition as for S_4^{kl}, but the arithmetic mean is created from three contributions.

It should be mentioned that the temporal data M_1^k and data scope M_5^k can also be represented as nonexclusive data pairs (past/future) and (low/high), respectively, which leads to a similar definition of S_1^{kl} and S_5^{kl} as for S_4^{kl}. Thus, for 5 out of 7 categorization dimensions, an identical similarity definition is used.

The classification of the autonomous control methods with respect to the newly defined categorization dimensions (see Table 1) is shown in Table 3. So far, the Bionic Manufacturing System method (Bio) is conceptual research only, and a classification is not possible at the moment. For the other 13 autonomous control methods, a classification according to the categorization dimensions is possible. These data are used to calculate the similarities S^{kl} for all pairs (M^k, M^l). The full similarity matrix is shown in Table 4. For symmetry reasons, only the upper triangle is shown, and the diagonal elements, which are always 100%, are omitted. The SRB1 method and the QLE method have a similarity of 100%. This does not mean that both methods are identical. The classification of the autonomous control methods is based on a rather rough scheme, and small differences in any of the categorization dimensions are not observable in the analysis.

Data from Table 4 are used to identify clusters of similar methods. A method cluster is defined as a set of autonomous control methods with all similarities S^{kl} larger than the threshold 71.43%, which corresponds to an identical classification for 5 out of 7 categorization dimensions. Four autonomous control method clusters could be identified (see Fig. 1 for a graphical representation). The categorization values for the four clusters are shown in Table 5. The clusters 1, 2, and 3 overlap, and 5 methods belong to more than one cluster. This indicates that all 8 methods (Ant, Bee, DD, OLTPR, Ph, QLE, SRB1, and SRB2) of the clusters 1, 2, and 3 are similar, which is confirmed by inspection of the categorization values (Table 5). Common features for the autonomous control methods of the clusters 1, 2, and 3 are

– Planning Step is 1
– Part–Machine communication is used
– Data Scope is either low or medium
– Decisions (Actor) are made by parts
– Data Storage is on the machine

The Pheromone Approach fulfills the similarity criterion to all methods of the clusters 1, 2, and 3, and the methods Ant, Bee, DD, OLTPR, QLE, SRB1, and SRB2 can be regarded as modifications of the Pheromone Approach although most methods have a completely different derivation. The methods LSIRP and DLRP create cluster 4, which deviates from cluster 1, 2, and 3 in the following categorization values

Table 3 Autonomous control methods classification

	Ant	C-Ant	Ph	Bee	SRB 1	SRB 2	QLE
Temporal data	Past	Past	Past	Past	Future	Past	Future
Planning steps	1	More	1	1	1	1	1
Artificial values	Dynamic	Dynamic	No	Static	No	No	No
Communication type	Part-machine	Part-part	Part-machine	Part-part, part-machine	Part-machine	Part-machine	Part-machine
Data scope	Low	High	Medium	Medium	Low	Low	Low
Actor	Part	Part	Part	Part	Part	Part	Part
Data storage	Machine	Part, machine	Machine	Machine	Machine	Machine	Machine

	DD	OLTPR	Market	Holonic	Bio	LSIRP	DLRP
Temporal data	Future	Hybrid	Past	Future	—	Past	Past
Planning steps	1	1	1	3	—	More	More
Artificial values	No	No	Dynamic	Dynamic	—	No	No
Communication type	Part-machine, part-part	Part-machine, part-part	Part-machine, central	Central, machine-machine	—	Machine-machine, central	Machine-machine, part-machine
Data scope	Medium	Medium	High	High	—	High	High
Actor part	Part	Part, machine	Part, machine, central	Machine, central	—	Machine	Part, machine
Data storage	Part, machine	Part, machine	Part, machine, central	Machine, central	—	Machine, central	Machine

- Planning Step is larger than 3
- Machine–Machine communication is used
- Data Scope is high
- Decisions (Actor) are made by machines

The methods C-Ant, Market, and Holonic cannot be assigned to any of the method clusters, and each method is a singular development so far.

The cluster analysis shows that many of the autonomous control methods developed so far bear much resemblance to each other despite their derivations from different origins. So far, rarely used categorization values could be the starting point for the development of new autonomous control methods that differ significantly from the existing ones, and the following features should be considered:

- Planning Step is larger than 1
- Artificial Values are used
- Communication is not restricted to Part–Machine
- Data Scope is high
- Decisions (Actor) is not restricted to parts
- Storage is not restricted to machine

4 Simulation studies

After classifying and analyzing the different methods, a comparison regarding their performance will be presented in the following. To compare different autonomous control methods, a generic and common production scenario is used. The shop floor consists of m parallel production lines where each production line comprises n machines M_{ij} ($i = 1, \ldots, m$, and $j = 1, \ldots, n$). Each machine has an input buffer B_{ij} with a maximum level of 40 items. K is the number of different products that can be produced by the production system.

At the source, the raw materials for each product type enter the system. The input frequencies for the raw materials are expressed by three temporally shifted sinus-shaped functions. This input model assumes a continuously varying number of incoming orders and reflects the dynamics within the production system. It is assumed that the different products have different operation times on the machines. The priority rule applied at the machines is first-come-first-served (FCFS) if no other rule is applied by the respective autonomous control. As the scenario is related to the classical job-shop factory layout, all production lines are connected at every stage. Every line is able to process every kind of product, and the parts can switch to a different line at each production stage. The product's choice of the next processing machine is determined by the applied autonomous control method.

Table 4 Autonomous control methods similarity in %

C-Ant	Ph	Bee	SRB 1	SRB 2	QLE	DD	OLTPR	Market	Holonic	LSIRP	DLRP	
60	79	82	71	86	71	56	58	63	36	32	49	Ant
	52	63	31	45	31	46	49	61	45	56	65	C-Ant
		82	79	93	79	77	80	56	29	54	70	Ph
			61	75	61	67	69	60	32	36	52	Bee
				86	100	85	73	35	36	32	49	SRB 1
					86	70	73	49	21	46	63	SRB 2
						85	73	35	36	32	49	QLE
							88	43	35	31	48	DD
								55	32	43	60	OLTPR
									63	50	50	Market
										54	37	Holonic
											83	LSIRP

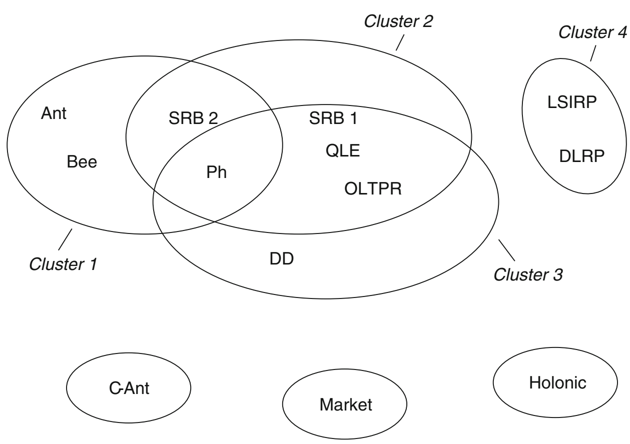

Fig. 1 Autonomous control method clusters

To compare the different methods, simulations were conducted for production scenarios from $m = 3$ to $m = 9$ with $m = n$ and $K = 3$ (products A, B, and C). The operation time was determined in relation to the simulation time. Product A had an operation time of 0.1%, product B of 0.5%, and product C of 1% of the total simulation time. To analyze the performance of different control methods, all methods that have been described in detail by their publication sources were selected. As the autonomous control methods are designed to cope with complex and dynamic manufacturing systems, the comparison is carried out for scenarios with and without machine breakdowns. The breakdowns of the machines represent an additional kind of dynamics and unpredictability of the system beside the input fluctuation. The breakdowns occurred randomly with a probability of 75% and a repair time of 1 min.

In order to determine the performance of the different autonomous control methods, several key indicators are measured. All results presented here are average values over five independent simulation runs. First, the overall output quantity during the simulation run is counted. Figure 2 shows the results. Except for the Ant and SRB2 algorithm, the investigated methods show a linear increase in the output quantity for both cases with and without machine failures. This shows the general performance but does not take into consideration the achievement of the different logistics targets. The logistics targets are short lead times, high due date reliability, high utilization, and low inventory [7]. In the simulation, the lead time is measured as the mean throughput time of the parts in the manufacturing system. The due date reliability is measured as the standard deviation of the throughput time, because it is assumed that low standard deviation indicates high predictability of lead time and results in high due date performance. The utilization is measured as percentage of time the machines are busy in relation to the total time capacity. The inventory level is measured as the average number of parts in the buffers in front of the machines.

Figure 3 shows the mean throughput time for the different methods. Without machine failures, the distribution appears evenly among the methods, having QLE, Holonic, LSIRP, and DLRP performing in a similar pattern, whereas Ant and SRB2 perform significantly worse (see Fig. 3a). In case of machine failures, SRB2 still performs worse than the other methods, but the difference compared to the other methods is smaller as displayed in Fig. 3b. The standard deviation of the throughput time shows again the distinct difference between the SRB2 and Ant method in relation to the rest of the investigated methods (see Fig. 4). However, again, the difference is smaller in the case of machine failures than that without machine failures. The two machine utilization graphs (see Fig. 5) show a similar pattern of performance where the drop in the performance in Fig. 5b is caused by the machine failure. The previously mentioned well-performing group of methods achieves to keep the utilization on a high level, whereas with an

Table 5 Common characteristics of the method clusters identified

Methods	Cluster 1 Ant, Ph, Bee, SRB 2	Cluster 2 Ph, SRB 1, SRB 2, QLE, OLTPR	Cluster 3 Ph, SRB 1, QLE, DD, OLTPR	Cluster 4 LSIRP, DLRP
Temporal data	Past	Different values	Different values	Past
Planning steps	1	1	1	>3
Artificial values	Different values	No	No	No
Communication type	Always including part-machine	Always including part-machine	Always including part-machine	Always including machine-machine
Data scope	Low/medium	Low/medium	Low/medium	High
Actor	Part	Always including part	Always including part	Always including machine
Data storage	Machine	Always including machine	Always including machine	Always including machine

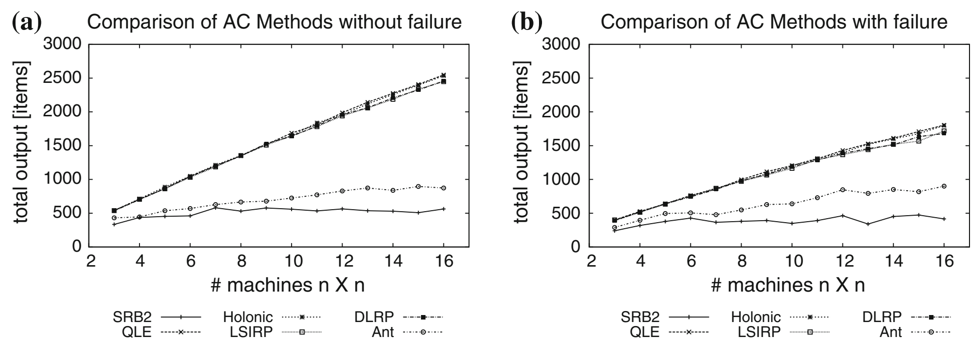

Fig. 2 Total output of simulation run. **a** Without machine failure, **b** with machine failure

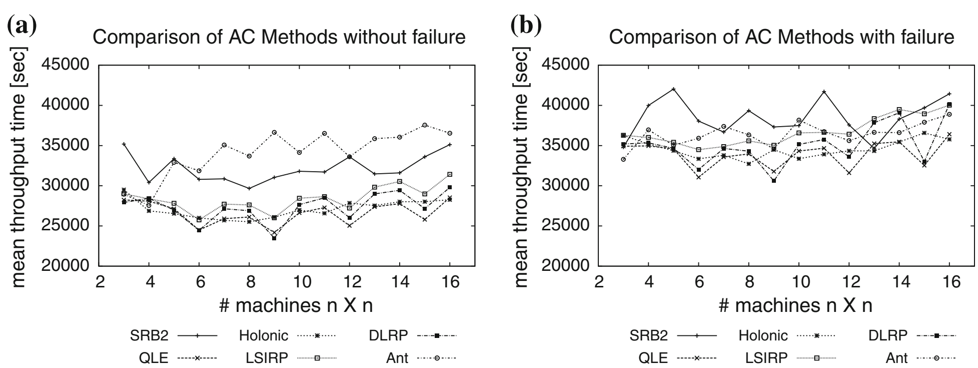

Fig. 3 Throughput time. **a** Without machine failure, **b** with machine failure

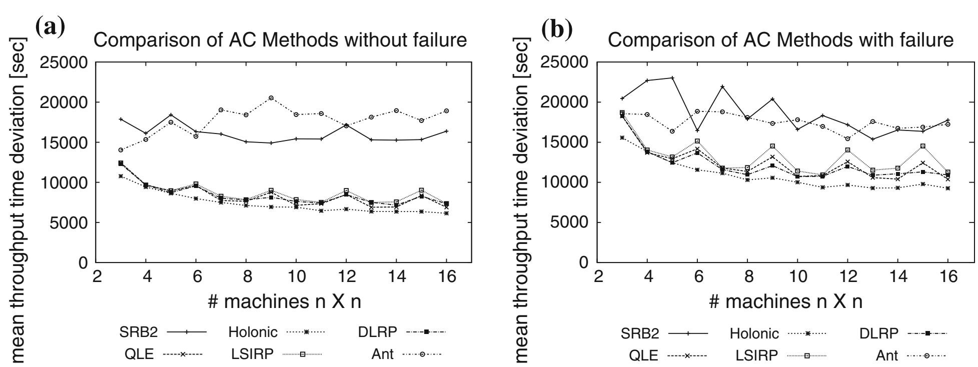

Fig. 4 Standard deviation of throughput time. **a** Without machine failure, **b** with machine failure

increasing size of the production system, the SRB2 and Ant method cannot keep utilization on the same level. Regarding work-in-process (WIP), only the Ant method shows a different, worse performing behavior, significantly for bigger production systems with machine failures (see Fig. 6).

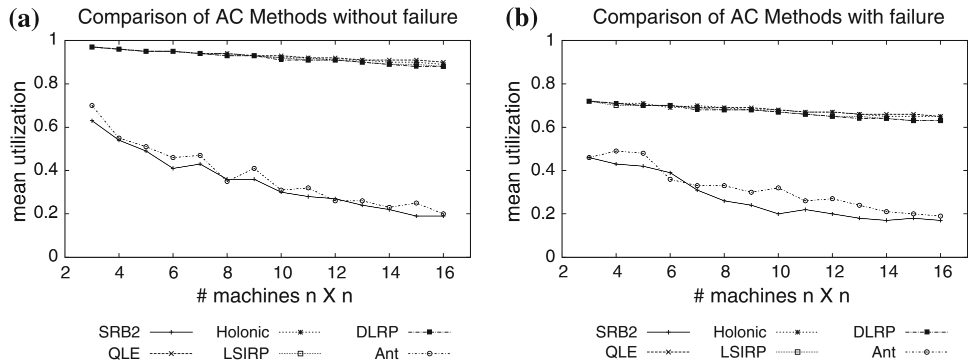

Fig. 5 Machine utilization. **a** Without machine failure, **b** with machine failure

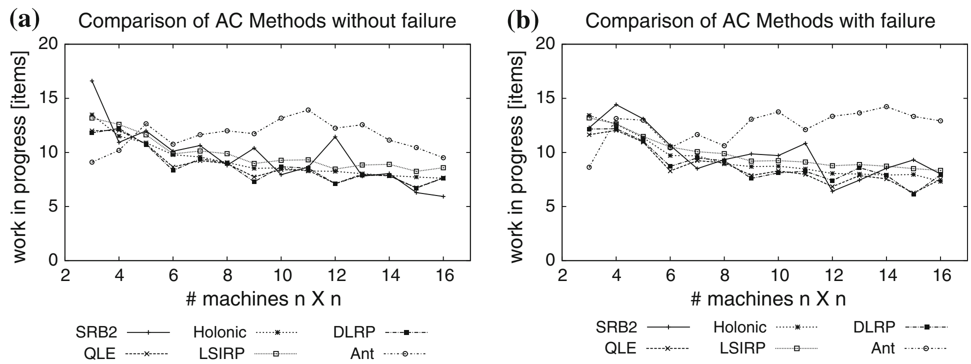

Fig. 6 Work-in-process. **a** Without machine failure, **b** with machine failure

Although the simulation results cannot finally prove the behavior of autonomous control methods according to the presented pattern, they definitely support the assumption that there is a systematic structure behind these methods. Two methods, namely Ant and SRB2, performed significantly different regarding nearly all logistics target indicators. Both methods are part of Cluster 1 and, at the same time, do not belong to Cluster 3 (see Fig. 1). All other tested methods, however, are distributed among the other clusters but behave similarly in the computer simulations. Another hint given by the simulation results is the autonomous control methods' behavior as a function of production network size. For all methods and all logistics target indicators, a relatively robust outcome can be observed. That means that in the presented scenario, the size of the production network does not have a major impact on the performance of the autonomous control methods.

5 Conclusion

This paper deals with the decision-making algorithms in autonomous control. A definition of the term autonomous control method was presented followed by a classification pattern for autonomous control methods in logistics. The pattern offers the possibility to identify the components that make up a certain autonomous control method and helps delimiting different methods from each other apart from their actual implementation. The survey showed 14 methods that have been developed in the recent years and classified them according to the presented pattern. As a result, four different clusters containing similar methods could be identified.

The simulation studies supported the assumption that there are similarities in logistics performance between certain groups of autonomous control methods, while the size of the production network does not significantly influence the methods' behavior.

The research group will extend the simulation studies in the future in order to gain deeper knowledge on the relation between autonomous control method characteristics and the logistics performance. Furthermore, it will focus on methods not included in the identified clusters, containing the so far not implemented characteristics.

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