Autonomous Production Control Methods - Job Shop Simulations

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Abstract. With the development of Industry 4.0 and the Internet of Things, autonomous production control is regarded as a feasible and promising approach for meeting the increasing challenges of complexity and flexibility. To implement autonomous production control methods in practice, a deeper understanding of their characteristics is necessary. This research provides a comparative perspective on existing methods. We study selected autonomous production control methods under various scenarios, and derive insights for the design of such systems in industrial practice.

Keywords: Autonomous production control · Autonomous control · Industry 4.0 · Production planning and control

1 Introduction

Confronted with the challenge of high complexity and volatility, manufacturers desire a higher degree of agility and flexibility in production planning to stay competitive. Autonomous production control appears to be a promising approach, as it enables logistic objects to process information and to render and execute decisions on their own [22]. It is able to handle dynamic and complex production circumstances by distributed and flexible coping of complexity. Through the development of Cyber-Physical Production Systems (CPS), 5G and Internet of things (IOT), autonomous production control has increasing potential and practical significance. Several autonomous production control methods have been introduced in last 20 years. Previous studies have shown that in certain settings autonomous production control can achieve logistics targets better than conventional production planning and control approaches [11].

Many open questions regarding the characteristics of autonomous production methods remain, and knowledge on these can significantly ease their implementation in practice. In this paper, we review the performance of selected autonomous

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production control methods through simulation, evaluating their performance characteristics. The remainder of this paper is structured as follows. In the next section, we provide an overview of selected autonomous production control methods. Subsequently, we describe the deployed methodology as well as our simulation results. The last section gives a conclusion on our main results as well as avenues for future research.

2 State of the Art

2.1 Autonomous Production Control

Production planning and control is an essential tool for any manufacturer. It addresses the allocation of resources to jobs and the subsequent creation of a schedule. In order to measure the performance of PPC, several indicators are used such as throughput time (TPT), work in progress (WIP), delay rate and utilization. Traditionally, a production schedule is created by a central planning authority. Autonomous production control however is based on a different approach: Every entity within the system, i.e. machines, resources, products, is equipped with a certain degree of *intelligence*. Through addition of computational power and connectivity combined with either a distributed control approach or a centralized control entity, each entity is able to monitor its environment and coordinate with other entities with the manufacturing system. This approach enables the system to be more agile and react quickly to any disturbance at its source. Thus, the system exhibits a high degree of flexibility, and is able to continuously adapt its schedule on a machine level [2].

2.2 Existing Autonomous Production Control Methods

Windt et al. divided autonomous production control methods into three approaches: rational, bounded rational, and combined strategies, which were derived from behavioral economics [20]. Examples of rational methods are QLE and DLRP. In these methods, objects exchange relevant information and decide according to future system states anticipation [4]. Biologically methods, such as Ant, PHE, Bee Foraging and Chemotaxis, belong to rational methods and use aggregated data from past events [12].

Scholz-Reiter et al. classified autonomous production control methods into two categories: local information methods and information discovery methods [12]. Local information methods gather and process only local information, such as QLE and PHE. Information discovery methods can collect relevant information from other objects, but not cover the whole system, such as DLRP.

2.3 Research Gap

There have already been studies on autonomous production control methods, comparing different approaches. For example, Scholz-Reiter et al. conducted a simulation study in 2009, but only compared three different autonomous control methods, namely QLE, DUE and PHE [11]. Windt et al. compared the performance of autonomous production control methods in two scenarios (with and without machine failure) by simulation [21]. As far as we know, the latest research in this field was conducted in 2011 by Becker et al. comparing six methods in 4 simulation scenarios: standard, full flexibility (suspend processing sequence to increase decision alternatives), increased load (increase processing time by 10%), both of full flexibility and increased load [2].

Table 1. Autonomous production control methods

Methods	c.f	Year	Key idea
Holonic manufacturing	[6]	1996	Machines bid to get jobs and get punished for delays
Market based	[17]	2000	Parts carry a shopping list of work needed to be done, parts auction for access to the machines
Ant	[3]	2001	Ants choose machines based on pheromone concentration
Pheromone based approach (PHE)	[1]	2006	Average throughput time is used as a pheromone
Due date method	[14]	2007	QLE and choose the most urgent due date in queue
Distributed logistics routing protocol (DLRP)	[19]	2007	Machines communicate best routes
Queue length estimator (QLE)	[13]	2007	Compares estimated waiting time at buffers
Bee foraging	[13]	2008	Based on the routes of previous parts
AMS-SCA	[9]	2012	Based on a swarm of cognitive and adaptive agents
Potential field (PF)	[8]	2012	The state of potential field depends on the attractiveness of the resource providing the service
Pheromone based coordination (PBC)	[18]	2012	The pheromone quantum of manufacturing cell is calculated inversely proportional to the cost, which guarantees a minimal cost to process the orders
Sudo	[16]	2013	A part agent chooses a machine, by the length of a job list and the conveyance cost
Integrated APC	[5]	2017	An integrated method considering order release, sequencing and capacity control to meet due date
Direct workload (DWL)	[4]	2018	Jobs are allocated only to the valid machine with the lowest workload

We expand on this by evaluating newly developed methods after 2011 in different simulation scenarios.

3 Methodology

3.1 Simulation Setup

The main simulation scenario is a make-to-order shop floor with five production stages. Within each stage, 6 functional equivalent machines are available as also reviewed by Schipper et al. [10]. These machines are denoted by $1, \ldots, 30$. However, these machines behaviour is not identical: Their processing times vary slightly, and their production cost is adjusted accordingly. This structure is visualized in Fig. 1.

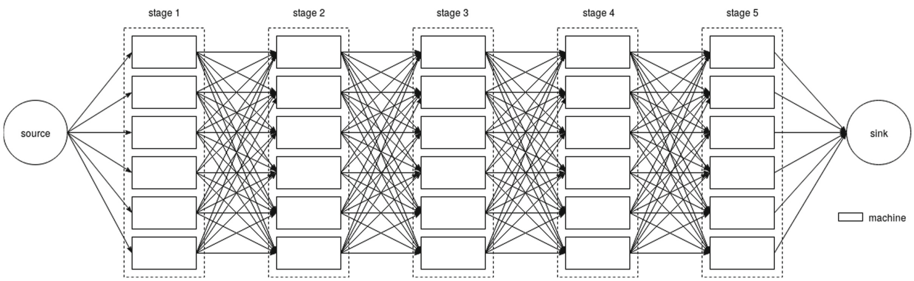


Fig. 1. Flexible network setup

In order to create a simulation that allows us to compare the aforementioned methods, we work with the following seven assumptions:

1. Each product needs to be processed in every stage, in ascending order.
2. The arrival of jobs follows a Poisson distribution with parameter λ, and the processing time of the machines follows an exponential distribution with parameter μ_i, $i \in \{1, \ldots, 30\}$.
3. The lot size per arrival is assumed to be one, which equals the capacity of all the machines. Machines process parts according to the first-come-first-served principle.
4. No limit on queue length.
5. Besides the machines, other resources are available at all times.
6. Setup times are included in the processing time, and transportation times between machines are negligible.
7. The cost of each processing process can be expressed as c_i, $i \in \{1, \ldots, 30\}$.

The parameters for the six machines within a stage are not equal, μ_i is set at the start for all simulation runs by adding a random offset to the base value for the machines of that stage.

This setup defines our standard scenario. We extend this setup by considering the possibility of machine breakdown. This results in two scenarios, for which the selected autonomous production control methods will be compared.

3.2 Selected Autonomous Production Control Methods

As a baseline for the simulation, we included the classical autonomous production control method of QLE. Furthermore, four new methods developed after 2010 were chosen: AMSSCA, PF, DWL and PBC, as they have not been reviewed in the previously mentioned studies. Additionally, they fulfill further criteria such as feasible implementation and comparability as well as a similar scope. Consequently, we compare the performance of methods for local decision making on dispatching, similar to most approaches [5]. We do not consider the autonomous production control method of Grundstein et al. as its scope is much wider in comparison, including dispatching, queue processing and capacity control [5]. In the remainder of this section we introduce each chosen method briefly.

The QLE method compares the full queue length of all viable processing paths, and chooses the shortest one. The queue length of a machine is given by the estimated total operation time of all parts within the queue of the machine. As such, this method uses expected information, and tries to minimize the corresponding expected waiting time.

The AMS-SCA method chooses the optimal machine based on a pheromone markers value among the available machines. The pheromone value p_i calculation considers the executing ability, processing time and machining cost of the corresponding machine i.

$$p_i = \frac{q}{\alpha_t * M_{ti}/M_{t_0 i} + \alpha_c * M_{ci}/M_{c_0 i}}, q \in \{0,1\}, \alpha_t + \alpha_c = 1$$

q denotes the executing ability of the machine i regarding the requested task. If a machine does not meet the requirements of the task, $q = 0$, and the pheromone is 0. Otherwise, $q = 1$. M_{ti} and M_{ci} represent the total time and machining cost of the task t at the machine i, respectively. $M_{t_0 i}$ and $M_{c_0 i}$ are the minimum total time and machining cost of the task t respectively in ideal situation. The factors α_t and α_c are the weight of the machining time and cost respectively. The weight can be changed to meet different goals of the company [9].

The key idea of the DWL method is to balance the workload of machines. The DWL method extends the QLE method. As an important difference, each machine has a workload limit, and a job is only allocated to a machine if the resulting workload of this allocation is within this limit. The workload considers expecting processing time of both jobs in the queue and the jobs being currently processed at the machine [4].

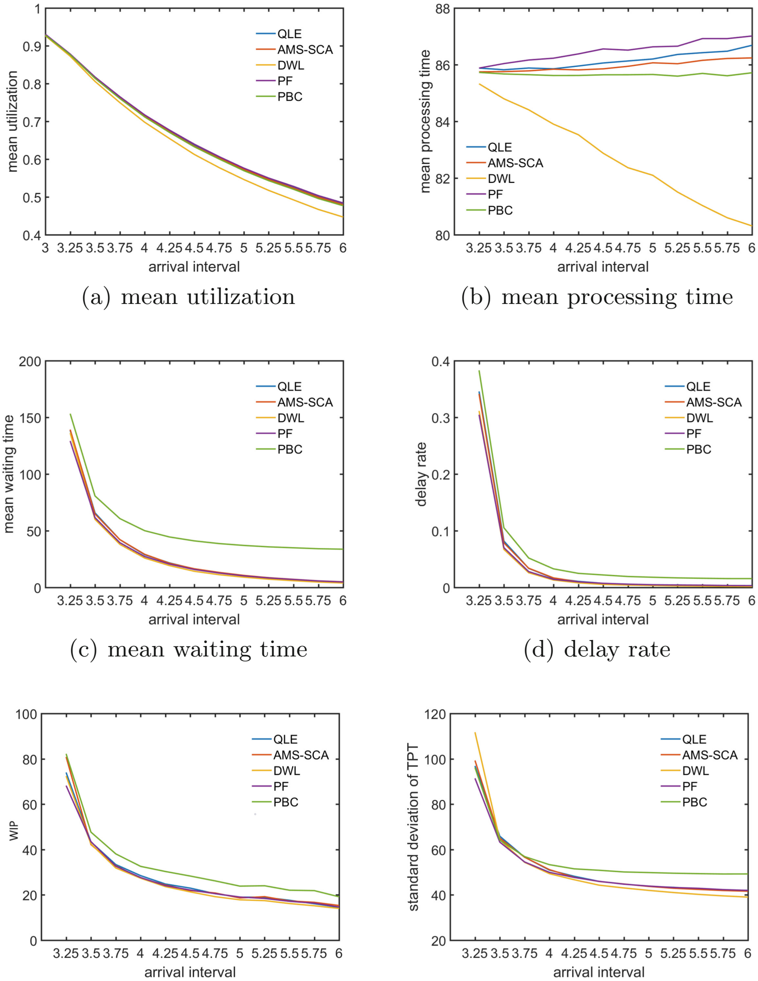
The PF method chooses the optimal machine by its attractiveness among the alternative machines. If a machine is broken now, its attractiveness is 0. Otherwise, its attractiveness equals to $a_i = \frac{1}{(1+WaitingTime)*Distance}$, where $WaitingTime$ refers to the expected waiting time if the job is assigned to machine i. $Distance$ refers to the distance between the current position of the job and the machine i. This method aims to minimizes the throughput time by reducing both travel and waiting time.

In the PBC method, the pheromone value is calculated inversely proportional to the cost. This cost consists of processing cost, storage cost and tardiness cost.

As such, this method takes due dates into consideration. It calculates a tardiness cost per machine, which is proportional to the length of the resulting due date delay.

4 Results

An overview of the performance of all methods in the standard scenario is given in Fig. 2. The mean utilization of all methods, visualised in Fig. 2(a) shows how close the studied methods are. With an arrival rate parameter of 3, the utilization



(a) mean utilization (b) mean processing time

(c) mean waiting time (d) delay rate

(e) WIP (f) TPT standard deviation

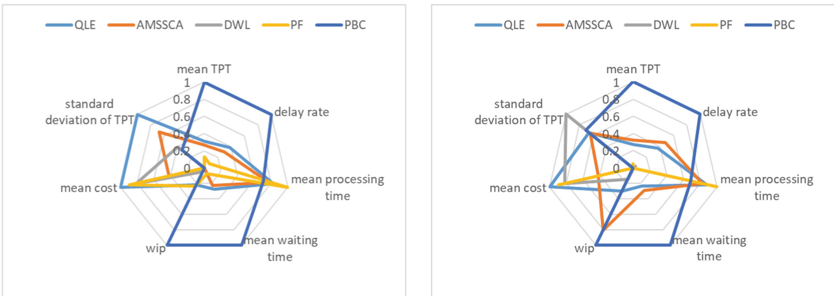
Fig. 2. Performance indicators for the standard scenario

is above 90% for all methods, decreasing for all methods when more and more jobs arrive. Notably, this decrease is worse for the DWL method, which can be explained by this methods tendency not to assign jobs to the slowest machines. In respect to the mean processing time though, a notable better performance can be seen for the DWL method. Regarding the remaining performance measures such as mean waiting time, delay rate, work in progress in throughput time the methods perform quite similar, with PBC often falling slightly behind. This is most likely due to the fact that it aims to pursue the lowest cost while remaining within the due date, hence it prefers the slow machines. This also results in the biggest WIP and delay rate, c.f. Figs. 2(e) and (d).

Taking the ranking for the studied metrics into a weighted measure of performance, the following method ranking emerges:

$$\text{DWL} > \text{PF} > \text{AMS-SCA} > \text{SCA} > \text{QLE} > \text{PBC}.$$

Lastly, Fig. 3 gives a comprehensive overview on the relative performance characteristics of each method in the standard scenario (Fig. 3(a)) as well as when introducing machine failure (Fig. 3(b)). For each performance dimension, the best performings method is used as reference point with a relative performance of one. Notably, these methods react differently to the introduction of machine failure. It highlights the superiority of DWL in time dimensions, the superiority of PBC regarding costs, as well as the acceptable performance of AMS-SCA in both areas. Furthermore, the high flexibility of PF in high workload scenarios with machines breakdown becomes apparent.



(a) standard scenario: $\lambda = 3.5$/ without breakdown/ fixed process

(b) breakdown: $\lambda = 3.5$/ failure rate=10^{-5}/ fixed process

Fig. 3. Overview on relative performance indicators

5 Conclusion

This paper gives an overview of four recently developed autonomous production control method. From a comparison of these methods in a job shop scenario we identify key characteristics and performance capabilities. Subsequently, these results can aid in a decision process for the application of autonomous control methods, depending on desired performance dimensions as well as time and cost constraints. This simulation however only covers a glimpse of possible applications for autonomous production control methods. For example, these methods can be used not only individually on the shop floor, but also coupled with central planning [15] or in combination, allowing online-switching with each other in order to adapt to different situations [7]. Furthermore, the dependence of autonomous production control performance on the underlying production network remains unclear. Also, the influence of the production networks size (i.e. number of machines, etc.) entices further research.

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