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IFAC PapersOnLine 54-1 (2021) 516–521

Distributed control for Industry 4.0 - A comparative simulation study

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Abstract: The recent decades have seen various market changes that industrial manufactures need to address. Increasing individualization of products and rapid demand fluctuations require new control approaches. In this article, we study the performance of centralized and distributed control approaches with regard to work in progress in a make-to-order environment. We utilize a multi-agent system in a discrete-event simulation to model several control approaches and provide various insights into potential benefits of distributed control concepts given rapidly fluctuating manufacturing demand.

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Keywords: Distributed control, manufacturing planning and control, make-to-order, multi-agent system, discrete-event simulation

1. INTRODUCTION

The manufacturing industry has been confronted with various challenges arising within the last decade, ranging from continuous globalization over new government regulations requiring more efficient production to changes in the market scenario. Customer demands are subject to substantial change and the expressed need for individualization requires adjustments of manufacturing objectives. Whereas previously large scale production with the prime objective of cost reduction was feasible, the production of individualized goods is not possible in the same manner. However, the advent of Cyber-physical systems (CPS) enables new and advanced manufacturing control architectures. Based on the inherent computing, sensing and network capabilities of CPS it is feasible for machines not only to act as order recipients of one centrally derived production schedule, but to distribute the traditionally centralized decision making authorities to these machines. Consequently, these machines can act autonomously and become *smart*. While such advanced manufacturing control architectures for Manufacturing Planning and Control (MPC) can offer interesting advantages over traditional centralized control concepts, they are not without drawbacks such as myopia. In this article, we compare several control approaches for a manufacturing network in a Make-to-Order (MTO) environment to address the manufacturing of individualized products. We consider challenges that industry 4.0 concepts often aspire to address, and consequently focus our comparison on work-in-progress (WIP) levels, manufacturing delays and computation requirements. The remainder of this article is structured as follows. In section 2 we give a brief overview on relevant literature streams and recent views regarding control concepts. Then, we present the applied methodology and our simulation framework in section 3. In section 4 we evaluate a look at our simulation results and compare them with findings from the literature. Lastly, we give a brief conclusion and outlook towards further research in section 5.

2. STATE OF THE ART

The concept of distributing decision making authority to autonomous entities within manufacturing network goes back to Aström (1985) and Koinoda et al. (1984). However, for distributed control to be feasible in practice, the technical requirements have only been fulfilled with the advent of CPS, driven by advances in microcontroller technology. This development has resulted in renewed interest in advanced distributed control concepts and acted as catalyst for research on such control approaches (Bertelsmeier and Trächtler, 2015; Wang et al., 2015; Jones et al., 2018; Romero et al., 2018; Bendul and Blunck, 2019; Antons and Arlinghaus, 2020a). Thus it has been possible and affordable to equip every machine, and to some extend even products, with sensors that enable these entities to capture the world around them, network interfaces which enable inter-entitys communication and lastly the computing capabilities required to process these local information and make appropriate decisions. Rooted in this distribution of control and local decision making are both the advantages and drawbacks of distributed control for autonomous manufacturing networks. On the one hand, the local information processing allows for a fast decision making process and consequently rapid responses to disturbances and fast information propagation which was noted early on (Duffie, 1990). Also, easy adaptability and extensibility have been associated with distributed control (Monostori et al., 2015). On the other hand, however, distributed control approaches have to address the inherent self-interest of autonomous entities and limited information horizon, which result in myopic behavior. This

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10.1016/j.ifacol.2021.08.059

phenomenon, in which autonomous entities take decisions that improve their own performance but are detrimental to the overall, global performance is referred to as myopia in literature (Trentesaux, 2009; Zambrano Rey et al., 2014). This myopia may be reduced by providing some level of centralized coordination (Antons and Bendul, 2019). The combination of elements from concepts of both distributed and centralized control leads to so called hybrid control approaches, in which the aforementioned entities only possess limited autonomy. Naturally, these concepts have been studied by several researchers from the field of production planning and control (PPC) and showed a variety of advantages and benefits, prominently in job shop settings (Bongaerts et al., 2000; Philipp et al., 2006; Scholz-Reiter et al., 2006; Meissner et al., 2017; Hussain and Ali, 2019). The multitude of available production routes in a job shop setting provides a suitable decision space for distributed control to take advantage of. The idea to address the increasing demand for highly customized products by utilizing advanced control approaches on manufacturing networks of CPS and apply a make-to-order principle was also studied in the context of industry 4.0 (Karaköse and Yetiş, 2017; Grassi et al., 2020; Alvarez-Gil et al., 2020). Furthermore, a variety of novel concept for human-machine interaction has been studied in the same context (Jones et al., 2018; Weichart et al., 2019). Across all research streams studying distributed control the application of multi-agent systems (MAS) has emerged as most suitable tool to model and analyze manufacturing networks (Caridi and Cavalieri, 2007; Morariu et al., 2014; Polyakovskiy and M'Hallah, 2014; Antons and Arlinghaus, 2020b).

3. METHODOLOGY

We utilize a discrete-event based multi-agent system to simulate an appropriate manufacturing network to study the influence of various centralized and distributed control approaches on WIP levels. In our simulation, we consider a set of production orders $\mathbb{O} = \{O_1, \dots, O_K\}$ that need to be processed. A single production order is denoted as O_k, $k \in \underline{K} := \{1, \dots, K\} \subset \mathbb{N}_{\geq 1}$ as lists of k_N consecutive jobs $[j_{k_1}, \dots, j_{k_N}]$, $N = N(k) \in \mathbb{N}_{\geq 1}$. We denote the set of all jobs as J. To complete a production order O_k, every job $j \in O_k$ of that production order need to be completed on a machine with matching capabilities. The jobs required for a production order depend on the type $t \in \underline{T} := \{1, \dots, T\}$ of product, hence the set of all production orders can also be viewed as union of disjoint subset $\mathbb{O} := \biguplus_{t \in \underline{T}} \mathbb{O}_t$. The manufacturing network consists of a set of in total Z machines $\mathbb{M} = \{M_1, \dots, M_Z\}$, $Z \in \mathbb{N}$. The manufacturing capabilities of every machine $M \in \mathbb{M}$ are determined by the machine type $\mathbb{M}_h$, $h \in \underline{H} := \{1, \dots, H\}$, $\mathbb{M} = \biguplus_{h \in \underline{H}} \mathbb{M}_h$. Every completion of a job $j \in J$ on a compatible machine $m \in \mathbb{M}$ requires a certain base amount of iteration dur_j, but may be extended by a lag time. This lag time represents the process time variability and is modeled a Poisson distribution with parameter λ_m for every machine. As we utilize a discrete-event simulation, we consider a discrete timeframe $I_A := \{0, \dots, I_{max}\}$ for a total of $I_{max} + 1$ iterations. Every machine is capable to process at most one job per iteration. In order to attain a valid schedule, we hence require a mapping of every job to a capable machine and iteration interval.

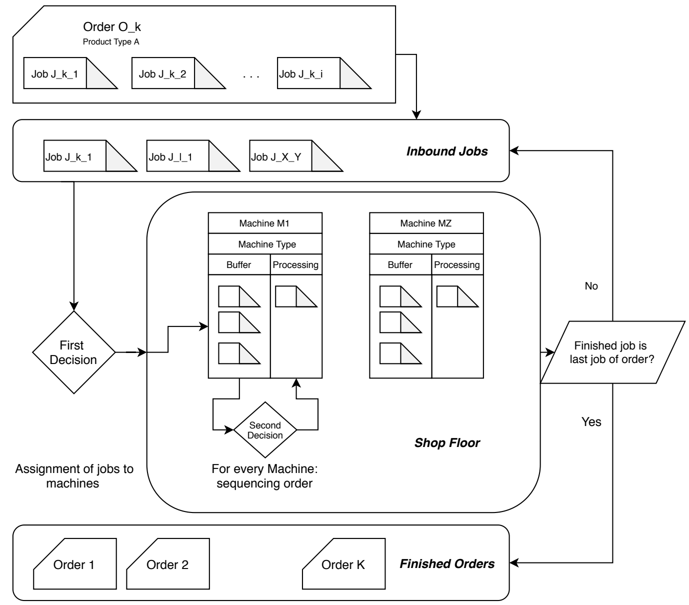

Fig. 1. Multi-agent based discrete event simulation

3.1 Simulation Framework

Within our simulation, every production order and every machine is represented as an agent. Depending on the utilized control architecture, these agents can either act fully autonomous, and thus make their own decisions based on local information, or they act as subordinates of a central controller and merely execute commands according to a globally derived mapping of jobs to machines and iterations. The process of this simulation is presented in Figure 1, where for every production order the first incomplete job is in the set of inbound jobs. For each of these first jobs, two decisions need to be made: On which machine is the job going to be processed, and what is the jobs position in the associated machines sequencing order. After a job has been completed, the production orders is finished in its entirety if all of its jobs have been completed, or the next consecutive job of the production order joins the set of inbound jobs. Whichever the case, this process requires an additional iteration to allow for the transport of a production order from one machine to another.

3.2 Distributed Control

In order to study the performance of advanced control concepts for autonomous entities, we utilize the established queue length estimation (QLE) decision function to assign jobs to machines. This decision is taken by the agent of the machines, and their decision function for the assignment of job j can be written as

$$\min_{M \in \mathbb{M}_{C_j}} \sum_{l \in J_M} dur_l, \qquad \text{(QLE)}$$

where $\mathbb{M}_{C_j}$ is the set of machine capable of processing job j and J_M the set of of jobs already assigned to machine M. The sequencing of the jobs J_M on machine M is decided by the agents corresponding to jobs in J_M, with priority being given to jobs with the most following consecutive jobs, and otherwise applying a first-in first-out (FIFO) principle. Since every decision is made based on local information, this process can be done by these autonomous entities. Due to the comparatively very little computation required for each agent it is possible to solve the distributed decision problems again and again, in every iteration.

3.3 Centralized Control

For the centralized control process, we consider all the available information for a global decision problem. We model this decision problem as mixed-integer linear problem (MILP) which is solved by a central controller which derives a valid mapping of product orders to machines and iterations. This mapping is then communicated to the agents representing machines and product orders, which in consequence act purely as subordinates, without exhibiting any decision autonomy. The used MILP can be found as MILP1 below, with the following decision variables defined in (12-16).

$$
\begin{array}{llll}
\min & f_z & & \text{(MILP1)} \\
\text{s.t.} & y_{jm} \leq \delta_{jm}, & \forall j \in J \ \forall m \in \mathbb{M} & (1) \\
& x_{ijm} \leq y_{jm}, & \forall j \in J \ \forall i \in I \ \forall m \in \mathbb{M} & (2) \\
& s_{jm} \leq y_{jm} I_{max}, & \forall j \in J \ \forall m \in \mathbb{M} & (3) \\
& t_{jm} \leq y_{jm} I_{max}, & \forall j \in J \ \forall m \in \mathbb{M} & (4) \\
& t_{jm} \leq c_{max}, & \forall j \in J \ \forall m \in \mathbb{M} & (5) \\
& \left(1 - \sum_{m \in \mathbb{M}} x_{ijm}\right) I_{max} \geq i - \sum_{m \in \mathbb{M}} t_{jm}, & \forall i \in I \ \forall j \in J & (6) \\
& -\left(1 - \sum_{m \in \mathbb{M}} x_{ijm}\right) I_{max} \leq i - \sum_{m \in \mathbb{M}} s_{jm}, & \forall i \in I \ \forall j \in J & (7) \\
& \sum_{j \in J} x_{ijm} \leq 1, & \forall i \in I \ \forall m \in \mathbb{M} & (8) \\
& \sum_{i \in I} \sum_{m \in \mathbb{M}} x_{ijm} = dur_j, & \forall j \in J & (9) \\
& \sum_{m \in \mathbb{M}} (t_{jm} - s_{jm}) + 1 = dur_j, & \forall j \in J & (10) \\
& t_{j_{k_n}} + 2 \leq s_{j_{k_{n+1}}}, & \forall O_k \in \mathbb{O} : (j_{k_n}, j_{k_{n+1}}) \in O_k & (11) \\
& c_{max} \in \mathbb{N}, & & (12) \\
& s_{jm} \in \mathbb{N}, & \forall j \in J \ \forall m \in \mathbb{M} & (13) \\
& t_{jm} \in \mathbb{N}, & \forall j \in J \ \forall m \in \mathbb{M} & (14) \\
& y_{jm} \in \{0,1\}, & \forall j \in J \ \forall m \in \mathbb{M} & (15) \\
& x_{ijm} \in \{0,1\}, & \forall j \in J \ \forall i \in I \ \forall m \in \mathbb{M} & (16)
\end{array}
$$

$$
\text{with } \delta_{jm} := \begin{cases} 1 & \text{if machine } m \in \mathbb{M} \text{ can process job } j \in J \\ 0 & \text{otherwise} \end{cases}
$$

Decision variable c_{max} denotes the makespan, i.e. the amount of iteration required to complete all jobs and thus all production orders. Decision variables y_{jm} encodes whether job j is processed on machine m and x_{ijm} whether this occurs in iteration i, while s_{jm} and t_{jm} encode at which iterations the processing of job j begins and ends on machine m, respectively (if job j is processed on machine m). Constraint (1) ensures that a job can only processed on a compatible machine. Constraints (2-7) link the decision variables appropriately, with Constraint (2) allowing the processing of a job on a machine in a specific iteration ($x_{ijm} = 1$) only if that jobs is processed on that machine ($y_{jm} = 1$). Constraints (3-4) permit a start and end time for the processing on machine ($s_{jm}, t_{jm} > 0$) only if the job is assigned to that machine ($y_{jm} = 1$). Constraints (6-7) make sure that jobs can only be processed on machines between their start and end iterations.. Constraint (8) ensures that every machines processes at most one job each iteration, while constraints (9) and (10) enforce the assignment of the required amount of machining iterations that each job requires to be completed. Lastly, constraint (11) guarantees that a job of a production order can only be processed once the previous job has been completed and an additional iteration for transport has passed.

$$f_1 := c_{max} \tag{17}$$

$$f_2 := \sum_{O \in \mathbb{O}} \sum_{m \in \mathbb{M}} t_{j_{k_N} m} \tag{18}$$

We analyze two different objective functions for this MILP, given as f_1 and f_2. The first objective function f_1 corresponds to minimizing the makespan of the entire production, hence the focus lies on the completion of all orders in the shortest amount of time. The second objective function f_2, however, minimizes the sum of completion time of production orders. The main difference between these objective functions is that the makespan considers the last completed order, while the second objective function considers the completion time of all orders.

In order to improve the performance of the utilized MILP solver and ensure the existence of a feasible solution we provide the MILP solver with an initial solution deriven by a simple heuristic. This heuristic can be found as Algorithm 1, and just assigns every job of every production order as early as machine capacity allows, sorted in descending order starting with the longest order.

Algorithm 1 Heuristic yielding upper bound for MILP1

Require: Set of orders, machines and iterations ▷

$$\hat{t_j} = \begin{cases} 0 & n = 0 \\ t_{j_{K_{n-1}}} & n > 1 \end{cases}$$

function HEURISTIC($\mathbb{O}, \mathbb{M}, I$)
  for $t \in \underline{T}$ sort by $N(t) + \sum_{l=1}^{N(t)} dur_l$ decreasing **do**
    for $O_k \in \mathbb{O}_t$ **do**
      for $j := j_{K_n}, n \in \{1, \ldots, N(k)\}$ **do**
        for $\bar{i} \in [max(0, \hat{t_j}), 2I_{max}]$ **do**
          for $m \in \mathbb{M} : \delta_{jm} = 1$ **do**
            if $\sum_{i \in \{\bar{i}, \bar{i}+p_j\}} x_{ijm} = 0$ **then**
              $x_{ijm} \leftarrow 1$ **for** $i \in \{\bar{i}, \bar{i} + p_j\}$
              $y_{jm} \leftarrow 1$
              $s_{jm} \leftarrow \bar{i}$
              $t_{jm} \leftarrow \bar{i} + dur_j$

3.4 Simulated Manufacturing Setting

For this article, we consider a manufacturing network with a total of 15 machine of ten different machine types. The manufacturing network is presented in Figure 2.

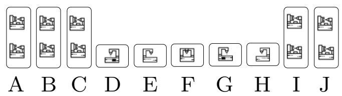

Fig. 2. Analyzed manufacturing network

This manufacturing network processes production orders of ten different types, that require different machining each. The required machining iterations for each job of every production order type is listed in Table 1.

Table 1. Required Machining Iterations per Production Order Type

$\mathbb{O}_T$	A	B	C	D	E	F	G	H	I	J
1	3	3	4	7	4				5	
2	3	3	4		4		8			3
3	3	3	4	7		3			5	
4	3	3	4	7		3				3
5	3	3	4		4			6	5	
6	3	3	4			3	8			3
7	3	3	4			3		6	5	
8	3	3	4		4			6		3
9	3	3	4	7			8		5	
10	3	3	4			3		6		3

While for each production order type the first three jobs are identical, each production order type then requires two different jobs of machining D-H. Lastly, depending on the product type the last job of each production order requires either machining of I or J. Notable, the amount of required iteration per job depends on the required machining type.

4. RESULTS AND DISCUSSION

We compare the performance of the three previously introduced control approaches with regard to relative work in progress, processing delays and runtimes for a total of $I_{max} = 200$ iterations in the manufacturing network presented in Figure 2. For the lag function that models processing delays we consider a Poisson distributions with $\lambda = \lambda_M \in \{0.1, 0.3, 0, .5\}$ for every machine $M \in \mathbb{M}$. For both centralized control approaches, we run the optimization process at the beginning of iterations $i \in \{0, 50, 100\}$ with an appropriate time limit. The distributed control approach, however, can run for every iteration as it only requires very little computation in comparison. As we model a production network that manufactures personalized products and has a high degree of make-to-order demand, we model the arrival of production orders as two different order types. The first type, referred to as regular orders, arrives at the iterations $\{0, 50, 100\}$ but their product type is uniformly randomized on the set of all product types. The second type of orders, which we refer to as irregular orders, also have their respective product type uniformly randomized on the set of all product types, but furthermore their arrival time is also uniformly randomized on the iteration interval $[0, 100]$. Thus these irregular orders correspond to make-to-order, and are consequently difficult for centralized control approaches to address, due to the inherent delay between order arrival and scheduling

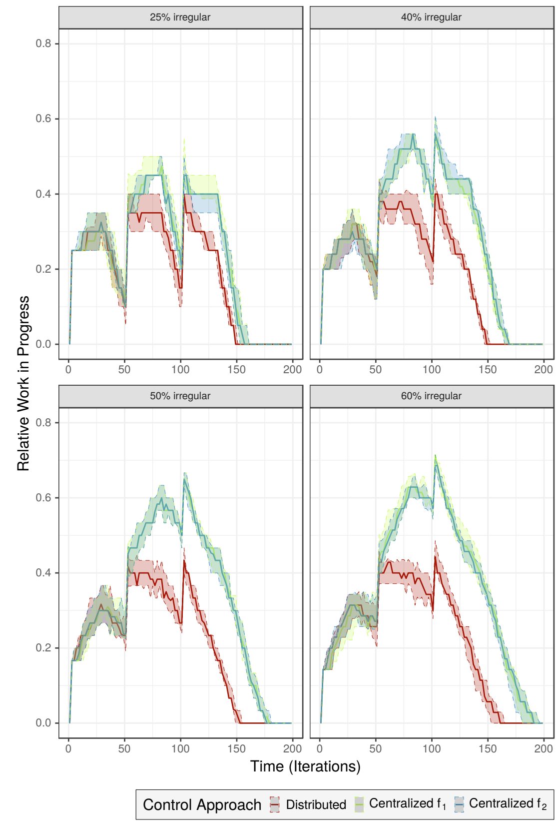

Fig. 3. Relative work in progress for distributed and centralized control approaches given different manufacturing demand regularity and $\lambda = 0.1$

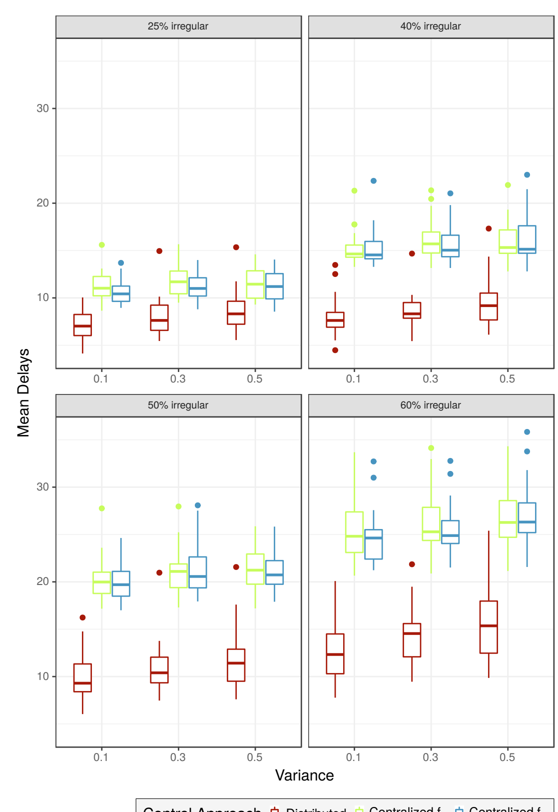

Fig. 4. Processing delays for distributed and centralized control approaches given different manufacturing demand regularity and $\lambda = 0.3$

of said order. For each setting, the simulations were run 20 times in order to address the random factors. Figure 3 shows the relative work in progress for all three control approaches given process time variation with lag parameter $\lambda = 0.1$. For all levels of irregular orders, the distributed approach (red) exhibits a lower degree of relative work in progress, compared to centralized makespan minimization (green) and centralized minimization of the sum of order completion times (blue). For both centralized control approaches we note a great deal of similarity, as even the lower and upper quartile ranges mostly overlap (displayed semi-transparent). Not only is the relative work in progress over time less for the distributed approach, but also the total amount of iteration necessary to complete all production orders is smaller. This difference in performance can be in part explained by the difference in optimization frequency: While the distributed control approach is able to schedule production orders within one iteration of their arrival time, the centralized approaches can only do so at fixed iterations. Especially in the first settings with a low degree of irregular orders the increase of WIP in the iterations $i \in \{50, 100\}$ is apparent, but not surprising due to the arrival of regular orders in these iterations.

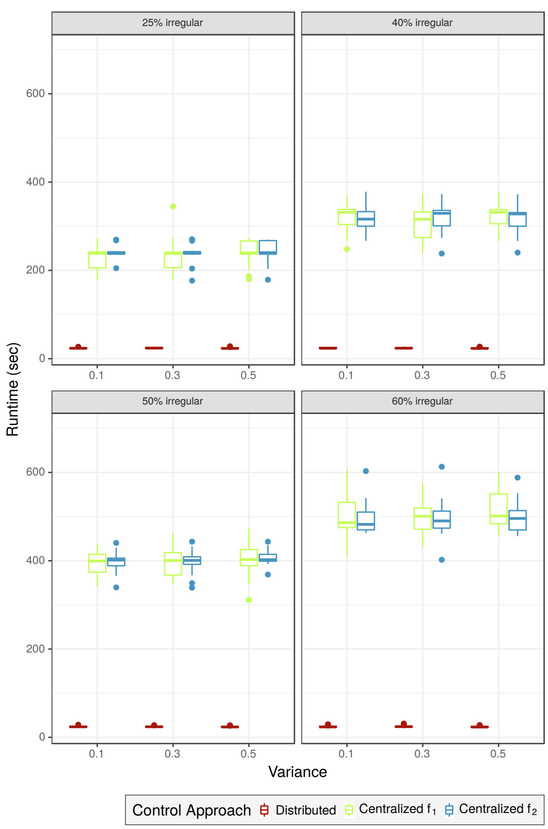

Fig. 5. Runtimes for distributed and centralized control approaches given different manufacturing demand regularity and $\lambda = 0.3$

In Figure 4 we present the mean delays of order processing, i.e. the sum of delays such as processing time variation, waiting for machining capacity and the delay between order arrival and order scheduling. While both centralized approaches show a similar performance in this regard, the distributed control approach exhibit notably smaller mean delays across all simulation settings. This again underlines the superior responsiveness of distributed control approaches and is mainly rooted in their ability to constantly optimize rather than only at selected iterations.

The requirements regarding computation are shown in Figure 5, which visualizes the runtime for all control approaches. While the distributed approach is capable of computing schedules within roughly 25 seconds for all simulation settings, the centralized approaches require already around 250 seconds for the lowest setting of irregular production orders. The computation time increases for every increase of irregular orders, up to approximately 500 seconds for 60% irregular orders. These results are similar to related studies in the literature (Scholz-Reiter et al., 2006; Polyakovskiy and M'Hallah, 2014), and underline the inherent advantage of distributed control approaches regarding response times.

5. CONCLUSION

In this article, we studied the performance of distributed and centralized control approaches in a manufacturing environment characterized by individualized products and a make-to-order environment. Such manufacturing environment permits distributed control approaches to leverage their inherent advantages such as rapid response times due to low computation requirements. These advantages allow for a lower WIP level throughout all simulated instances, while simultaneously exhibiting shorter throughput times due to faster allocation of production orders to machines compared to traditional, centralized approaches. These observations from the literature are supported by our simulation results presented in section 4, and the application of novel distributed control approaches may increase several performance characteristics in current industrial manufacturing settings within a make-to-order environment suitable for individualized products. For the application of such novel control approaches, however, several open question remain, regarding influence of information availability on the performance of distributed and centralized manufacturing planning and control. Furthermore, the degree to which distributed control approaches can beneficially evaluate local information without compromising on their inherent advantage of quick responsiveness may provide structural knowledge for the design of control architectures. Lastly, the influence of manufacturing network structures on the utility of distributed control requires further research to facilitate a fundamental understanding. Thus, several avenues for further research invite exploration of many facets of novel distributed control approaches.

REFERENCES

Alvarez-Gil, N., Rosillo, R., de la Fuente, D., and Pino, R. (2020). A discrete firefly algorithm for solving the flexible job-shop scheduling problem in a make-to-order manufacturing system. *Central European Journal of Operations Research*. doi:10.1007/s10100-020-00701-w.

Antons, O. and Arlinghaus, J.C. (2020a). Designing decision-making authorities for smart factories. *Procedia CIRP*, 93, 316–322.

Antons, O. and Arlinghaus, J.C. (2020b). Modelling autonomous production control: A guide to select the most suitable modelling approach. In *Dynamics in*

Logistics, Lecture Notes in Logistics, 245–253. doi:10.1007/978-3-030-44783-0_24.

Antons, O. and Bendul, J.C. (2019). The impact of information and communication flow structures on logistics performance in industry 4.0 production systems with distributed control. In *EurOMA19*.

Aström, K.J. (1985). Process control - past, present, and future. *IEEE Control Systems Magazine*, 5(3), 7.

Bendul, J.C. and Blunck, H. (2019). The design space of production planning and control for industry 4.0. *Computers in Industry*, 105, 260–272. doi:10.1016/j.compind.2018.10.010.

Bertelsmeier, F. and Trächtler, A. (2015). Decentralized controller reconfiguration strategies for hybrid system dynamics based on product-intelligence. In *2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA)*, 1–8. IEEE. doi:10.1109/ETFA.2015.7301527.

Bongaerts, L., Monostori, L., McFarlane, D., and Kadar, B. (2000). Hierarchy in distributed shop floor control. *Computers in Industry*, 43(2), 123–137. doi:10.1016/S0166-3615(00)00062-2.

Caridi, M. and Cavalieri, S. (2007). Multi-agent systems in production planning and control: an overview. *Production Planning & Control*, 15(2), 106–118. doi:10.1080/09537280410001662556.

Duffie, N.A. (1990). Synthesis of heterarchical manufacturing systems. *Computers in Industry*, 14(1-3), 167–174. doi:10.1016/0166-3615(90)90118-9.

Grassi, A., Guizzi, G., Santillo, L.C., and Vespoli, S. (2020). A semi-heterarchical production control architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 24, 43–46. doi:10.1016/j.mfglet.2020.03.007.

Hussain, M.S. and Ali, M. (2019). Distributed control of flexible manufacturing system: Control and performance perspectives. *International Journal of Engineering, Applied and Management SciencesParadigm*, 54(2), 156–162.

Jones, A.T., Romero, D., and Wuest, T. (2018). Modeling agents as joint cognitive systems in smart manufacturing systems. *Manufacturing Letters*, 17, 6–8. doi:10.1016/j.mfglet.2018.06.002.

Karaköse, M. and Yetiş, H. (2017). A cyberphysical system based mass-customization approach with integration of industry 4.0 and smart city. *Wireless Communications and Mobile Computing*, 2017, 1–9. doi:10.1155/2017/1058081.

Koinoda, N., Kera, K., and Kubo, T. (1984). An autonomous, decentralized control system for factory automation. *Computer*, 17(12), 73–83.

Meissner, H., Ilsen, R., and Aurich, J.C. (2017). Analysis of control architectures in the context of industry 4.0. *Procedia CIRP*, 62, 165–169. doi:10.1016/j.procir.2016.06.113.

Monostori, L., Valckenaers, P., Dolgui, A., Panetto, H., Brdys, M., and Csáji, B.C. (2015). Cooperative control in production and logistics. *Annual Reviews in Control*, 39, 12–29. doi:10.1016/j.arcontrol.2015.03.001.

Morariu, O., Raileanu, S., Morariu, C., and Borangiu, T. (2014). Multi-agent system for heterarchical product-driven manufacturing. In *2014 IEEE International Conference on Automation, Quality and Testing, Robotics*, 1–6. IEEE. doi:10.1109/AQTR.2014.6857897.

Philipp, T., Böse, F., and Windt, K. (2006). Evaluation of autonomously controlled logistic processes. In *Proceedings of 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering*, 347–352. CIRP, The International Academy for Production Engineering.

Polyakovskiy, S. and M'Hallah, R. (2014). A multi-agent system for the weighted earliness tardiness parallel machine problem. *Computers & Operations Research*, 44, 115–136. doi:10.1016/j.cor.2013.10.013.

Romero, D., Jones, A.T., and Wuest, T. (2018). A new architecture for controlling smart manufacturing systems. In *2018 International Conference on Intelligent Systems (IS)*, 421–427. IEEE.

Scholz-Reiter, B., Freitag, M., De Beer, C., and Jagalski, T. (2006). The influence of production networks' complexity on the performance of autonomous control methods. In *Proceedings of the 5th CIRP International Seminar on Computation in Manufacturing engineering*, 317–320.

Trentesaux, D. (2009). Distributed control of production systems. *Engineering Applications of Artificial Intelligence*, 22(7), 971–978. doi:10.1016/j.engappai.2009.05.001.

Wang, L., Törngren, M., and Onori, M. (2015). Current status and advancement of cyber-physical systems in manufacturing. *Journal of Manufacturing Systems*, 37, 517–527. doi:10.1016/j.jmsy.2015.04.008.

Weichart, G., Fast-Berglung, A., Romero, D., and Pichler, A. (2019). An agent- and role-based planning approach for flexible automation of advanced production systems. *2018 International Conference on Intelligent Systems (IS)*. doi:10.1109/IS.2018.8710546.

Zambrano Rey, G., Bonte, T., Prabhu, V., and Trentesaux, D. (2014). Reducing myopic behavior in FMS control: A semi-heterarchical simulation–optimization approach. *Simulation Modelling Practice and Theory*, 46, 53–75. doi:10.1016/j.simpat.2014.01.005.