ScienceDirect

IFAC PapersOnline CONFERENCE PAPER ARCHIVE

IFAC-PapersOnLine 49-31 (2016) 161–166

Dynamic Switching Mechanism to Support Self-organization in ADACOR Holonic Control System

Paulo Leitão [*,**] **José Barbosa** [*]

[*] *Polytechnic Institute of Bragança, Campus Sta Apolónia, 5300-253 Bragança, Portugal, Email: {pleitao,jbarbosa}@ipb.pt*
[**] *LIACC – Artificial Intelligence and Computer Science Laboratory, Rua Campo Alegre 1021, 4169-007 Porto, Portugal*

Abstract: Evolvable control systems face the demands for modularity, decentralization, reconfigurability and responsiveness pointed out by the Industrie 4.0 initiative. In these systems, the self-organization model assumes a critical issue to ensure the correct evolution of the system structure into different operating configurations. ADACOR holonic manufacturing control architecture introduces an adaptive production control mechanism that balances between two states, combining the optimization provided by hierarchical structures with agility and responsiveness to condition changes offered by decentralized structures. This paper describes the switching mechanism that supports this dynamic balance and particularly the local and global driving forces for the self-organization model. The proposed model was experimentally tested in a small scale production system.

Keywords: Self-organization, Holonic systems, Switching mechanism.

1. INTRODUCTION

The factories of the future in the era of the fourth industrial revolution demand the digitalization of manufacturing by introducing the data connectivity, advanced data analytics, human-machine interaction and digital physical conversion (Bauer et al., 2015). This is aligned with the Industrie 4.0 initiative (Kagermann et al., 2013), promoted by the German government and followed by several other countries around Europe, and the Industrial Internet initiative (Lin et al., 2015), promoted by the US government in articulation with several major players, In this context, the control architecture, which assumes a critical role in the system performance in terms of production efficiency and response to change, is pushed into a new dimension. The traditional installations are based on rigid, monolithic control structures, which are not anymore enough to address these emergent requirements, namely in terms of agility, reconfigurability and responsiveness to unexpected disturbances. The current trend in this field points out the distribution of the control over a network of several autonomous and intelligent entities, integrating cyber and physical counterparts, as sustained by the Cyber-Physical Systems (CPS) concept (Lee, 2008).

Multi-agent systems (MAS) (Wooldridge, 2002) and Holonic Manufacturing Systems (HMS) (Deen, 2003) are suitable approaches to realize the CPS solutions. In fact, these paradigms support the complete decentralization and distribution of manufacturing control functions by autonomous and cooperative intelligent entities, aiming to achieve better flexibility, agility and responsiveness to condition changes. Since the use of flat control architectures introduces good reaction to disturbances but degrades the global production optimization, the challenge is to combine their best features with the best characteristics of hierarchical structures, aiming to achieve agility to emergency without compromising the global optimization. In the last years, several approaches aiming this challenge were reported in the research literature, namely ADACOR (Leitão and Restivo, 2006), ORCA-FMS (Pach et al., 2014) and Pollux (Jimenez et al., 2016). In these evolvable architectures, a crucial issue is the switching mechanism that supports the evolution of the organizational structure.

One of these notably self-organized manufacturing control architectures is ADACOR (ADAptive holonic COntrol aRchitecture for distributed manufacturing systems) (Leitão and Restivo, 2006) that uses the holonics principles (Koestler, 1969) to propose an adaptive control approach that is neither completely decentralized nor hierarchical, but balances between a more centralized approach and a flatter approach. This dynamic, agile and adaptive control approach is possible due to the implementation of a self-organization model, inspired in biological systems, and driven by local and global forces. As in the similar approaches, a crucial issue in this adaptive mechanism is the switching mechanism, which ensures a fast but reliable transition between the two states, avoiding the decrease of the system performance by remaining in a non-optimal state no longer than needed.

This paper describes the ADACOR switching mechanism that supports the adaptive production control, and particularly details the local and global driving forces for the implementation of the self-organization model. The proposed approach was experimentally tested in a small scale production system, confirming the applicability of the switching mechanism by analysing its sensibility to several parameters, namely the re-establishment time and the frequency of disturbances.

The rest of the paper is organized as follows: Section 2 overviews the adaptive production control approach proposed by ADACOR and Section 3 details the description of the switching mechanism associated to the self-organization model.

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.12.179

Section 4 describes the experimental testing and analyses the achieved results, and at last, Section 5 rounds up the paper with the conclusions and points out the future work.

2. ADACOR SELF-ORGANIZING MODEL

The ADACOR adaptive holonic architecture proposes the decomposition of manufacturing control functions into a community of autonomous and cooperative holons, representing the manufacturing components. Four types of holons were identified according to their functionalities and objectives (Leitão and Restivo, 2006): *product holons* (PH) represent the catalogue of products produced by the production system, *task holons* (TH) are responsible to manage the orders for the production of product instances, *operational holons* (OH) manage the behaviour of shop floor resources, such as operators, robots and quality control stations, and *supervisor holons* (SH) introduce coordination and global optimization in decentralized control structures.

ADACOR innovates by introducing a dynamic adaptive control approach that considers insights from the self-organization principles, which is a powerful concept found in several domains, such as biology (e.g., ants foraging and birds flocking), chemistry (e.g., the Belousov-Zhabotinsky reaction), physics (e.g., 2nd thermodynamics law) and social organization (e.g., traffic and pedestrian walk in crowed environments). Basically, self-organization is a process of evolution where the development of emergent, novel and complex structures takes place primarily through the system itself, and normally triggered by internal forces. These forces require the integration of autonomy and learning capabilities within entities to reach, by emergence, a behavior that is not programmed or defined a priori (Massotte, 1995), providing the ability of an entity/system to adapt itself to prevailing conditions of its environment (Thamarajah, 1998).

Having this in mind, ADACOR dynamic adaptive control approach uses a self-organization model to combine the best features of hierarchical and heterachical control approaches, i.e. using a hierarchical approach in presence of stable operating conditions, and a more heterarchical approach in presence of unexpected events and modifications. For this purpose, the adaptive control behaviour balances between the stationary and transient states, as illustrated in Fig. 1.

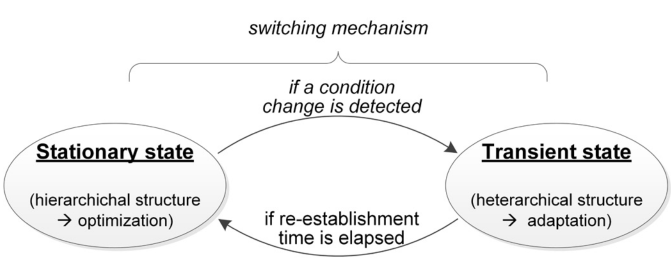

Fig. 1. Adaptive behaviour balancing between stationary and transient states.

In *stationary state*, the holons are organized in a hierarchical structure to achieve the global optimization, with the supervisor holons coordinating clusters of operational holons, and interacting directly with the task holons during the resource allocation process. Supervisor holons, as coordinators and having a wider perspective of the system, elaborates optimized schedule plans that are proposed to task and operational holons under their coordination domain. The task and operational holons see these proposals as advices, having enough autonomy to accept or reject the proposed schedules.

In case of a condition change, e.g., due to a machine failure or a rush order, the holons self-organize into a heterarchical structure, providing agility and responsiveness to the emergency. In this *transient state*, the task holons interact directly with the operational holons to achieve an alternative schedule plan that mitigates the impact of the disturbance. The system should remain in the transient state as shorter as possible and return to the stationary state when the disturbance is recovered.

This adaptive control approach allows to reach significant benefits in terms of combining optimization when running in stable scenarios with agility and responsiveness to condition changes when running in emergent situations, as illustrated in Fig. 2.

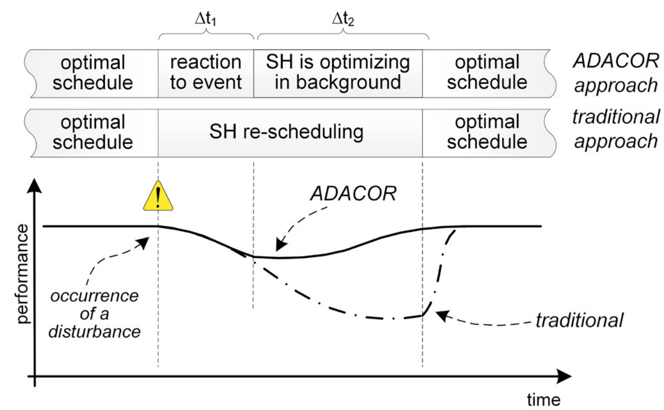

Fig. 2. Evolution of ADACOR and traditional approaches over the time.

In fact, the traditional centralized, rigid and monolithic approaches need to elaborate a re-schedule, which usually takes a significant amount of time, being the performance significantly degraded until a new optimized schedule is calculated. In opposite, ADACOR applies a fast reaction to disturbances, even that non-optimal, which strongly mitigates the impact of the performance degradation. Posteriorly, the individually achieved non-optimal plans are optimized by the supervisor holons (running in background). The benefits of ADACOR are more significant as high is $\Delta t2/\Delta t1$, and how often is the number of perturbations.

3. DETAILING THE ADACOR SWITCHING MECHANISM

The self-organization model that implements the switching between the stationary and transient states is supported by local driving forces, namely the autonomy factor and the learning capability associated to individual holons, complemented with global driving forces that propagates the emergence and the need for reorganization. This section details the ADACOR switching mechanism, describing the local and global self-organization driving forces.

3.1 Local Driving Force: Autonomy Factor

The autonomy factor, α, is a parameter associated to each ADACOR holon that reflects its degree of autonomy, being regulated by the function, $\alpha = f(\alpha, \tau, \rho)$, where τ is the re-establishment time, which is the estimated recovery time, and

ρ is the pheromone parameter, which indicates the level of impact of the disturbance (Leitão, 2009). This function uses a fuzzy rule-based engine that considers simple discrete binary variables for the autonomy factor and the pheromone parameter. Particularly, the autonomy factor uses a simple discrete binary variable comprising the states {Low, High}, where {Low} means a low adaptation appetence, and {High} means a stimulus for adaptation to mitigate the impact of perturbations. The cardinality of the discrete set associated to the autonomy factor has strong impact in the dynamic adaptation mechanism: as higher is the number of discrete values, as smoother will be the adaptation procedure. However, a high number of discrete values makes the adaptation mechanism more complex. A discrete variable is also used for the pheromone parameter, comprising the states {Very Low, Low, Medium, High, Very High}.

An example of the set of rules that regulates this function is (Leitão, 2008):

IF $\rho >= HIGH\ AND\ \alpha == LOW$ THEN
$\quad alpha := HIGH\ AND\ load\ \tau\ AND\ selectsNewBehaviour$
IF $\rho >= HIGH\ AND\ \alpha == HIGH\ AND\ \tau == ELAPSED$
$\quad \alpha := HIGH\ AND\ reload\ \tau$ THEN
IF $\rho <= LOW\ AND\ \alpha == HIGH\ AND\ \tau == ELAPSED)\ THEN$
$\quad \alpha := LOW\ AND\ selectsNewBehaviour$

The occurrence of an unexpected disturbance, e.g., a machine failure or a delay, is represented in the the pheromone parameter according to the potential impact that the disturbance may cause (proportional to the distance to the epicentre of the disturbance occurrence). A {High} value triggers the change of the autonomy factor to {High}, the load of the re-establishment time and the selection of a behaviour that supports the reorganization into the heterarchical structure.

When the re-establishment time has elapsed, if the pheromone is still active, i.e. {Medium}, {High} or {Very High}, which means that the disturbance is not completely recovered, the holon remains in the transient state and the re-establishment time value is reloaded; if the pheromone has already dissipated, i.e. presenting {Very Low} or {Low} values, which means that the disturbance is already solved, the holon can return to the stationary state, changing the autonomy factor to {Low} and re-organizing into the original hierarchical structure.

The autonomy factor is complemented by learning capabilities embedded in individual holons that allows to identify opportunities to evolve and the best way to evolve.

3.2 Global Driving Force: Propagation Mechanisms

Besides the local driving forces, the global system self-organization is only reached if the distributed agents have stimulus that drive their local self-organization capabilities. ADACOR defines a pheromone-like mechanism to propagate the need for adaptation recalling the stigmergy concept, which is used in biology to describe the influence of persisting environmental effects of previous behaviours in the current behaviour.

Adapting this powerful biological concept, in case of emergence, the need for re-organization is propagated through the deposit of a pheromone to the neighbour supervisor holons (as ants deposit pheromones in the environment). The quantity of pheromone is proportional to the forecasted impact of the disturbance, and reflects the estimated re-establishment time (forecasted according to the type of disturbance and the historical data). When the disturbance takes more time to recover than the initially expected, the odor is reinforced (similar to the pheromone odour).

Posteriorly, subordinated holons will sense this information (like ants sense the pheromones odour), and take their own actions to re-organize and propagate this need to neighbour holons. The intensity of the odour associated to the pheromone becomes smaller with the increase of the levels of supervisor holons according to a flow field gradient (similar to the distance in the original pheromone techniques).

3.3 Synchronizing and Optimizing the Dynamic Scheduling

Since the adaptive production control approach considers two different stages, different scheduling strategies are also considered: i) a centralized scheduling, to be embedded in supervisor holons, to reach optimized and efficient production performance taking advantage of the hierarchical organization of the holons, and ii) a dynamic re-scheduling approach performed during the transient state, based on a multi-round Contract Net Protocol (CNP) (Smith, 1980), which extends the original schema with some features, such as multiple iterations, contract of partial quantities and penalty conditions in the contract.

When the system returns to stationary state, after to recover from the disturbance, the current schedule being implemented at the shop floor is the one achieved by the dynamic distributed schema. This aggregation of individual local schedules are not optimized, since the main objective was to achieve alternative plan in a very short time. Since the supervisor holons are now returning to their coordination function, they need to synchronize and optimize the elaborated individual schedules, as illustrated in Fig. 3.

For this purpose, they collect the individual schedules achieved during the transient state, synchronize them and proceed with an optimization procedure by applying a proper schedule optimization algorithm. In this phase, and since this process is running in background and will take some time, part of the schedule (the nearest one) is frozen and is not considered in the schedule optimization. The frozen time is determined according to the estimated calculation time to elaborate the optimized scheduling, considering learning mechanisms based on the past information. At the end, supervisor holons will send the optimized schedules for their sub-ordinated holons that accept them since they are running again in a stable operation.

3.4 Switching Mechanism Working in Practice

The adaptive production control running in practice is exemplified in Fig. 4. In normal operation, the system is running in the stationary state, with the holons being organized in a hierarchical structure, each one having a {Low} autonomy factor. In this state, supervisor holons generate optimized production schedules that are proposed to the subordinated holons that are following them as advises.

When a disturbance is detected, e.g., the machine breakdown for OH3, the holon tries to recover locally. If unsuccessfully, the holon re-schedules the assigned orders as fast as possible. For this purpose, the OH1 increases its autonomy factor to {High} and propagates the need for re-organization by depositing a pheromone to the neighbour supervisor holon. Note that the pheromones intensity is the estimated re-establishment time, calculated according to the type of disturbance and to the

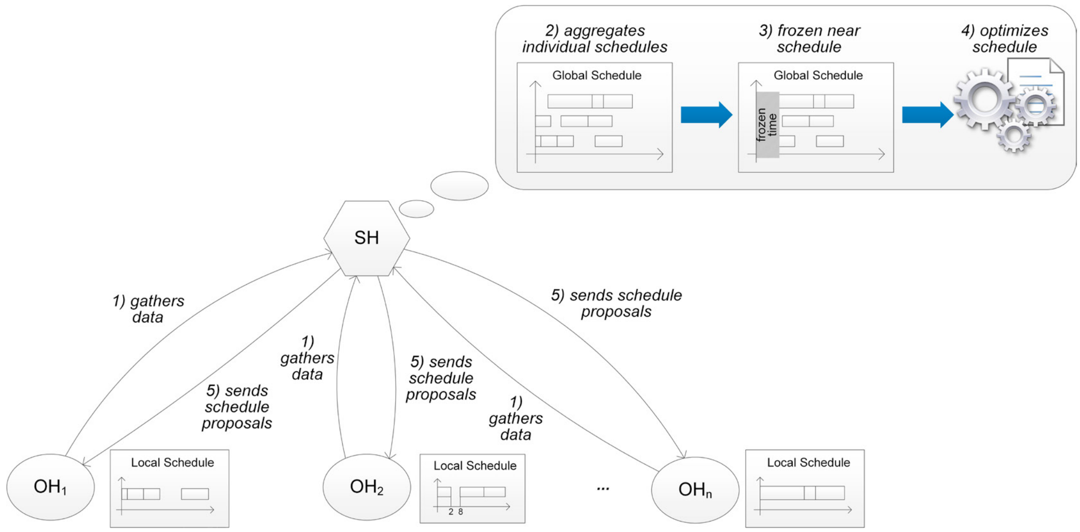

Fig. 3. Synchronization and optimization of individual schedules by SHs.

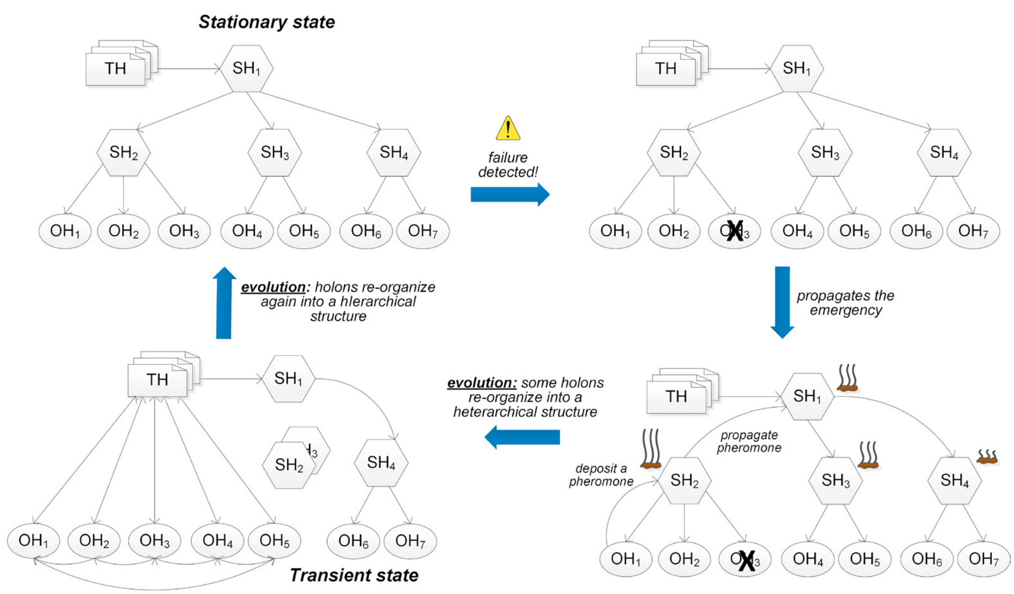

Fig. 4. Self-organization in ADACOR working in practice (Leitão and Restivo, 2006).

historical data. The other holons that sense the pheromone decide to increase or not their autonomy factors according to the decision function previously described (and consequently decide if re-organize or not), and propagate the re-organization emergence to the neighbour supervisor holons. The intensity of the pheromone becomes smaller with the increase of the levels of supervisor holons, according to a defined flow field gradient. In Fig. 4, the holons OH1 to OH5 decide to re-organize, but holons OH6 and OH7 decide to remain in the same structure since the pheromones intensity is low.

In the transient state, the task holons interact directly with the operational holons to achieve an alternative schedule plan in a faster manner. Supervisor holons continue elaborating and proposing optimized schedules, but since the holons have now {High} autonomy factors, they will reject the proposals.

The holons remain in the transient state only during the necessary time to recover from the failure. In fact, after the disturbance recovery, OH1 ends the reinforcement of the pheromone, and the re-establishment time is adjusted using proper learning mechanisms. At this moment, the other holons do not sense anymore the pheromone and reduce their autonomy factors, returning the system to the previous control structure.

3.5 Equilibrium in the Adaptation Mechanism

In dynamic and self-organized systems, some instability may occur resulting from the unpredictable behavior emerged from the non-linear interactions among the distributed entities and also from the nervousness of the individual entities (naturally each individual entity changes intentions during its life-cycle, being the nervousness quantified by the frequency that this phenomenon occurs). Aiming to push the system into its limits, taking advantages of the benefits provided by the theory of chaos (Hogg and Huberman, 1991), but maintaining it under control to ensure stability, the system nervousness should be properly balanced to allow the system dynamic evolution into different structures maintaining high performance levels.

In the ADACOR approach, the stability in the switching mechanism can be affected by several parameters, namely the frequency of failures and the re-establishment time. In particular, the re-establishment time may have a strong impact in the system nervousness, which requires its dynamic adjustment by using learning mechanisms. In fact, the switching problem may fall into two different situations. The first one happens when the system switches back too quickly not given enough time for the holons to completely re-organize, not responding effectively to the unpredicted event. A second scenario may happen when the system remains in the transient state more time than the necessary, which means that the system is running in a non-optimal manner more time than desired.

4. EXPERIMENTAL TESTS AND ANALYSIS OF RESULTS

The adaptive production control model was tested in an experimental case study aiming to determine the impact of the establishment time in the switching mechanism.

4.1 Case Study Description

The experimental case study is a small-scale production system, illustrated in Fig. 5, composed by one IRB 1400 ABB robot that executes the transfer operations between the machines, two punching machines, two indexed lines and one pneumatic machine, all supplied by Fischertechnik. Additionally, a warehouse is used to store raw parts and a human operator performs visual inspection operations to verify if the processing operations are performed according to the specifications.

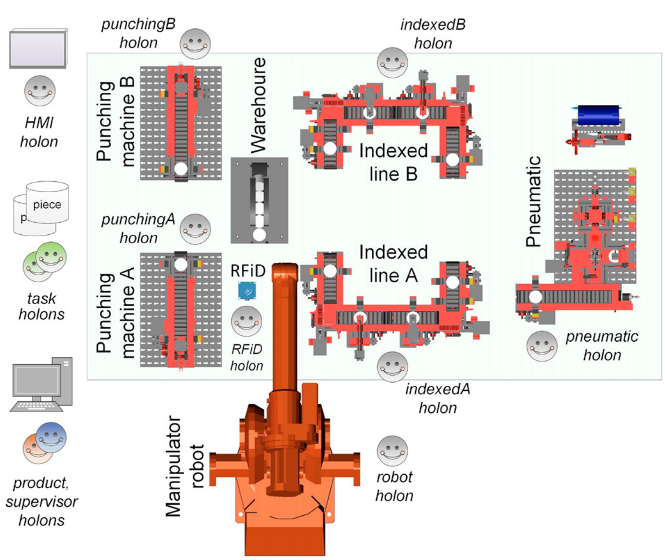

Fig. 5. Layout of the small-scale production system.

The set of available skills in each resource at the small-scale production system is represented in Fig. 6. Two different parts can circulate in the system, i.e. partA and partB, each one having a particular process plan, also illustrated in Fig. 6.

The circulation of parts within the flexible production system is tracked by a radio-frequency identification (RFiD) reader, which allows to uniquely identify each part, and consequently to know the process plan that should be executed.

Resource	**{Skill, time}**
Punching machine A	{punch_1, 5}
Punching machine B	{punch_1, 7}
Indexed line A	{drill_1, 7}, {drill_2, 6}
Indexed line B	{drill_1, 5}, {drill_2, 9}
Pneumatic	{pneumatic, 10}
RFiD reader	{read, 2}
Inspector	{inspection, 3}

Sequence	**Part "A"**	**Part "B"**
#1	punch_1	drill_1
#2	pneumatic	drill_2
#3	drill_1	punch
#4	drill_2	inspection
#5	inspection	-

Fig. 6. Resource skills and process plans.

4.2 Analysis of Experimental Results

The holonic solution was implemented by using the agent technology and particularly the JADE framework (Bellifemine et al., 2007). The ecosystem included 8 OHs (HMI, punchingA, punchingB, indexedA, indexedB, RFiD, pneumatic and robot), 2 PHs (partA and partB), 1 SH and several THs depending of the batch size. The operational agents are interconnected with the physical devices, i.e. robots and PLCs controlling the Fischertechnik stations, by using OPC Unified Architecture (OPC UA). A genetic algorithm scheduling approach was embedded in the SH to provide optimized plans.

Fig. 7 illustrates the experimental results considering the analysis of the influence of some parameters in the ADACOR switching mechanism, particularly the probability of failure and the re-establishment time. A scenario comprising a batch of 5 parts A with 3 parts B and the introduction, 60 seconds later, of a second batch of 2 parts A and 2 parts B were considered.

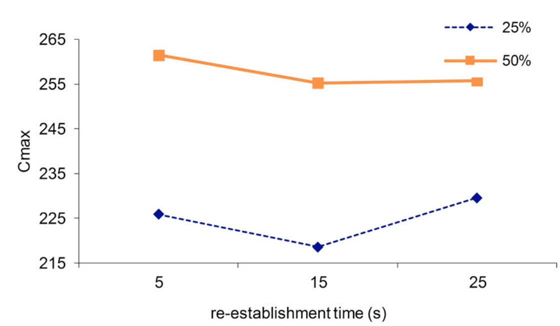

Fig. 7. Experimental results considering different failures rates and re-establishment times.

The experimental results clearly show the influence of the re-establishment time in the system performance, namely the makespan (Cmax), reflected in the curves for the both failure rates, i.e. 25% and 50% in the *punchingA* machine. The analysis of the figure shows an inflection in the Cmax curve namely for 15 seconds. In fact, if the re-establishment time is too big, the system take too much time to return to the original structure and then is running a lot of time in a non-optimal operation. In opposite, if the re-establishment time is too short, the system is continuously reacting and adapting and consequently is too chaotic and running in an non-optimal operation. Note that the proper re-establishment time may be dependent of the operation conditions and the use case particularities, being required a dynamic and on-the-fly adjustment of this value, e.g., by using machine learning mechanisms.

The same experiments were performed for a batch size comprising an order for 8 parts A and 7 parts B (see Fig. 8).

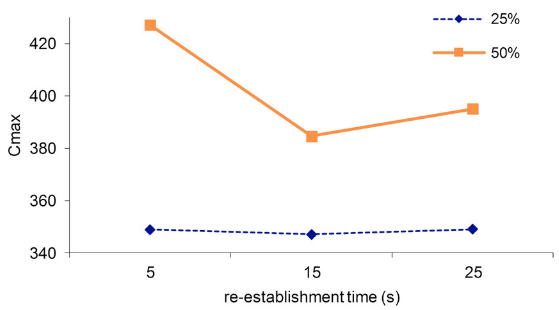

Fig. 8. Experimental results considering a different batch size.

These experimental results for a different batch size confirm and re-inforce the identified pattern in the evolution of the system performance, and particularly the influence of the re-establishment time.

5. CONCLUSIONS

The self-organization capability exhibited by ADACOR holons allows to balance the control structure between different control structures, reaching an adaptive control approach that combines the agile reaction to disturbances with the global optimization. The self-organization model is achieved by considering local driving forces, namely the autonomy factor and learning capabilities associated to individual holons, and global driving forces, namely the pheromone-like propagation.

The experimental testing considering a small-scale production system allowed to validate the proposed adaptive production control approach, and particularly the switching mechanism associated to the self-organization model. Particularly, it was demonstrated the capability of the system to re-organize into different control configurations according to the need to react promptly to condition changes. It was also verified the influence of some parameters in the performance of the switching mechanism, namely the failure rate and the re-establishment time. In particular, the re-establishment time assumes a crucial role to ensure a proper balance between control structure, while maintaining the system stable and under control.

Future work is being devoted to develop a more open and truly self-organization mechanism designed by ADACOR^2 (Barbosa et al., 2015) that explores the entire structural configuration space. This approach, although introducing a higher complexity level, allows the system to either evolve smoothly by using behavioural self-organization or to respond more drastically to high level disturbances by using structural self-organization.

REFERENCES

Barbosa, J., Leitão, P., Adam, E., and Trentesaux, D. (2015). Dynamic Self-organization in Holonic Multi-agent Manufacturing Systems: The ADACOR Evolution. *Computers in Industry*, 66, 99–111.

Bauer, H., Baur, C., Camplone, G., and et. al. (2015). Industry 4.0: How to Navigate Digitization of the Manufacturing Sector. Technical report, McKinsey Digital.

Bellifemine, F., Caire, G., and Greenwood, D. (2007). *Developing Multi-Agent Systems with JADE*. Wiley.

Deen, S. (ed.) (2003). *Agent-Based Manufacturing: Advances in the Holonic Approach*. Springer Verlag Berlin Heidelberg.

Hogg, T. and Huberman, B. (1991). Controlling chaos in distributed systems. *IEEE Transactions on Systems, Man, and Cybernetics*, 21, 1325–1332.

Jimenez, J.F., Bekrar, A., Trentesaux, D., and Leitão, P. (2016). A Switching Mechanism Framework for Optimal Coupling of Predictive Scheduling and Reactive Control in Manufacturing Hybrid Control Architectures. *International Journal of Production Research, in press*.

Kagermann, H., Wahlster, W., and Helbig, J. (2013). Securing the Future of German Manufacturing Industry: Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0. Technical report, ACATECH – German National Academy of Science and Engineering.

Koestler, A. (1969). *The Ghost in the Machine*. Arkana Books, London.

Lee, E.A. (2008). Cyber Physical Systems: Design Challenges. In *Proc. of the 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC'08)*, 363–369.

Leitão, P. (2008). A Bio-Inspired Solution for Manufacturing Control Systems. In A. Azevedo (ed.), *Innovation in Manufacturing Networks*, volume 266, 303–314. IFIP International Federation for Information Processing.

Leitão, P. (2009). Holonic Rationale and Bio-inspiration on Design of Complex Emergent and Evolvable Systems. In A. Hameurlain, J. Küng, and R. Wagner (eds.), *Transactions on Large Scale Data and Knowledge Centered Systems, Lecture Notes in Computer Science*, volume 5740, 243–266. Springer.

Leitão, P. and Restivo, F. (2006). ADACOR: A Holonic Architecture for Agile and Adaptive Manufacturing Control. *Computers in Industry*, 57(2), 121–130.

Lin, S.W., Miller, B., Durand, J., Joshi, R., Didier, P., and et al., A.C. (2015). Industrial Internet Reference Architecture. Technical report, Industrial Internet Consortium (IIC). URL `http://www.iiconsortium.org/IIRA-1-7-ajs.pdf`.

Massotte, P. (1995). Self-organization: A New Approach to Improve the Reactivity of the Production Systems. In *Proc. of the IEEE Intl Conference on Emergent Technologies for Factory Automation (ETFA'95)*, 23–32.

Pach, C., Berger, T., Bonte, T., and Trentesaux, D. (2014). ORCA-FMS: A Dynamic Architecture for the Optimized and Reactive Control of Flexible Manufacturing Scheduling. *Computers in Industry*, 65(4), 706–720.

Smith, R. (1980). Contract net protocol: High-level communication and control in a distributed solver. *IEEE Transactions on Computers*, C-29(12), 1104–1113.

Thamarajah, A. (1998). A Self-organizing Model for Scheduling Distributed Autonomous Manufacturing Systems. *Cybernetics Systems*, 29(5), 461–480.

Wooldridge, M. (2002). *Introduction to Multi-Agent Systems*. John Wiley & Sons.