Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 51-11 (2018) 1255–1260

A Negotiation-based control approach for disturbed industrial context

Tsegay Tesfay MEZGEBE[1,2], Hind BRIL EL HAOUZI[1,2], Guillaume DEMESURE[1,2], Andre THOMAS[1,2]

[1]*Université de Lorraine, CRAN, UMR 7039, Campus Sciences, BP 70239, 54506,*
Vandœuvre-lès-Nancy cedex, France
[2]*CNRS, CRAN, UMR7039, France*
E-mail {tsegay-tespay.mezgebe, hind.el-haouzi, guillaume.demesure, andre.thomas}@univ-lorraine.fr

Abstract: It is now accepted that using the multi-agents system (MAS) augments the reactivity to treat disturbances within flexible manufacturing system. Each agent could have different capability (evolution, learning, etc.) and the whole physical and control system, based on the agent interaction, could lead emerging behaviors to dynamically adapt a production schedule. Intelligent control algorithms shall be used to define these variables and all smart entities within their environment have to continuously negotiate for their final common goal. This paper proposes a negotiation-based reactive control approach to deal with the variability on manufacturing processes. A simulation experiment on the basis of full sized academic experimental platform was used to test how the negotiation-based reactive control approach could optimize priority based product sequencing. The product and resource agents have been built to negotiate considering different production performance measures. This has been done with expectations that the applicability of the negotiation-based reactive decision making process will be more adaptable to a production change than myopic decisions.

Keywords: Control Protocol, Distributed Reactive, Intelligent Decision, Multi-Agents System, Negotiation-based Control

1. INTRODUCTION

In today's volatile market world, manufacturing industries are facing a severe pressure to deal with the increased variability of manufacturing systems, especially with the control of their lead times, due dates, and work-in-process mainly impacted by the queue times. Meanwhile, the paradigm of Industry4.0, which gears towards increasingly individualized customer requirements (Koch et al. 2014), is urging these industries to focus on technological advancement by integrating their intelligent resources, products, and augmented human. As a result of this pressure, industries are continuously seeking for new control systems that enable them to respond quickly. For instance, as a response to unpredictable disruptions, they could look for proactive control (eliminating problems before they have chance to appear), reactive control (responding to past or current events after they have happened), or interactive control (associates with technologies allowing human-machine interaction) approaches (Fig. 1). The last approach realizes the capability of smart entities to create a system such that production components within the system not only interact to each other but also adapt and/or learn.

In addition to manufacturing industries, research institutions have been also showed the interest of designing and employing negotiation heuristics for multi-agent manufacturing systems (Shen et al. 2006). For example, when schedules acquire a reputation for rapid invalidity because of frequent changes, using dynamic rescheduling methods to conquer such disturbances is proved to be crucial. To do this, intelligent optimization protocols shall be used to define different variables and all entities within the environment have to continuously negotiate for final decision. In this paper, negotiation-based reactive control approach (NRC) between product and resource agents cooperating to set best sequential priority-based production process has been presented to show its advantage over pure reactive control approach (PRC). In pure reactive control approach, product agents are active and well known of their own state but resource agents are mostly dormant that simply waits for instructions from product agents and hence the overall performance of the system is decided by product agents only.

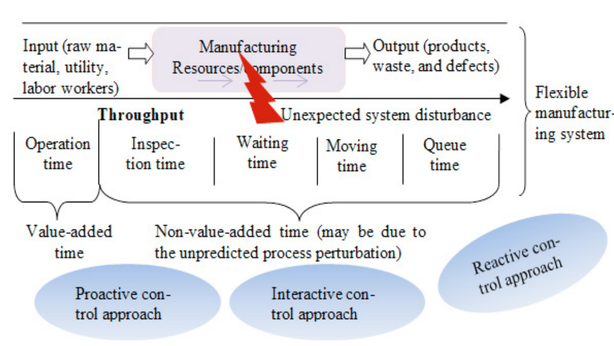

Fig. 1. Three control approaches in manufacturing systems

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2018.08.360

MATLAB simulation experiments on the basis of TRACILOGIS test-bed platform was used to test how these two production decision approaches affect the priority based routing sheet. Resource utilization, product tardiness, and makespan as performance measures and work-in-process queue between a machine and its upper stream as constraint are considered during the experiment. The work proposed in this paper is the continuity of Mezgebe et al. (2018). The experimental scenario is significantly improved with a greater analysis of performance criteria on higher instances. The test on the TRACILOGIS Platform is still in progress.

The rest of the paper is organized as follow. Section 2 elaborates related works on negotiation-based reactive control approach. After this, Section 3 demonstrates the negotiation scenario between product and resource agents using different control protocols and mathematical models. Section 4 analyses the comparative results of the two control approaches. Finally, Section 5 forwards further remarks mainly relating to the role of consensus algorithm for optimizing distributed reactive control by coupling with central entities.

2. REVIEW OF RELATED MATERIALS

In the manufacturing control systems survey, it is well accepted that multi-agents system model is a good way to deal with disturbances observed within a shop floor. Without being exhaustive, some intelligent manufacturing control systems based on MAS could be cited: Leitão (2009), Herrera et al. (2016), Saharidis et al. (2006), Anderson & Bartholdi (2000), Mezgebe et al. (2018) etc. Successively, many researchers are still working on this control system as it employs different models depending on the nature of real time events. Multi-agent system (MAS) is a system that consist a society of agents that could potentially collaborate with each other with capability to perceive, reason, and communicate to solve problems (Wooldridge, 2009; Botti & Giret, 2008; Isern et al., 2011). Wooldridge (2009) has raised two questions that could always come when one needs to implement these cooperative agents: (a) How one can build agents that are capable of autonomy? (b) How one can build agents that are capable of cooperating with other agents?

In answering these questions, an agent has to cooperate with other nearby agents in several different ways. Validating this cooperation, Isern et al. (2011) has presented that even though agents are perceived as autonomous entities, they are also members of a society and have to exchange information with other agents and maintain some relationships at an organizational level. Consequently, the mere presence of multiple agents makes the environment appear dynamic from the point of view of each agent, with the control system they follow, typically distributed reactive control (Vlassis 2003). On the other hand, to create an environment that provides an infrastructure specifying communication and interaction protocols of agents, Weiss (1999) has pointed out the knowability, reactivity, and sociability of agents as basic characteristics of multi-agent environment. Meanwhile, Holvoet & Valckenaers (2006) have stated that the applicability of MAS is characterized by their large scale in terms of number of agents & physical distribution, their very dynamic nature, and their complex functional & non-functional requirements. To sustain these characteristics, different application models and control architectures could always take appropriate attention as they bring amplified benefits. Examples are ant colony (Valckenaers & Van Brussel, 2015; Blum & Sampels, 2004; Liang & Smith, 2004; termite colony (Pannequin R. & Thomas A. (2012), potential field (Pach et al., 2014), and negotiation between intelligent entities (Tonino, 2002; Rahwan et al., 2003; Kraus, 1997), among many others.

From these applicability models, the negotiation of agents has taken viable attention. For instance, Dimopoulos & Moraitis (2006) has stated that individual agents can generate and execute their plans independently. However, as they operate in the same environment, conflicts may arise and hence they need to coordinate their course of action. (Zambrano et al., 2011; Wooldridge, 2009) have also indicated that negotiation among agents is foreseen to host a robust-predictive-reactive scheduling and also to tackle myopia. On the other hand, Tonino et al. (2002) has illustrated the investigations of different automated agent negotiation approaches including game-theoretic, heuristic-based, and argumentation-based approaches. Globally, three of them emphasize the importance of exchanging information between agents in order to mutually influence their behaviours. The game-theoretic approach helps to determine an optimal strategy by analyzing the interaction of agents as a game rule between identical and self-interested participants (Nagarajan & Sošić, 2008; Rosenschein & Zlotkin, 1994) but unbounded computational resources as limitation. To overcome this limitation, the heuristic approach has come with the principle of "produce good enough rather than optimal outcomes" (Aydogan et al., 2013; Kraus, 2001). Irrespective of its advantage, this approach is also known for its sub-optimal outcome as it does not examine the full space of possible outcomes (Jennings et al. 2001).

Argumentation-based negotiation approach has evolved to overcome the knowledge limitations of agents in game-theoretic and heuristic negotiation approaches. As it has been surveyed by Rahwan et al. (2003), this negotiation approach allows agents to exchange additional information, or to argue about their beliefs & other's mental attitudes during the negotiation process. Agents accept, reject, or critique an offer proposed by other agent until they agree on this offer. Generally, the work of Rahwan et al. (2003) has magnified that argumentation-based negotiation approach has been gained increasing popularity for its potential ability to overcome the limitations of other conventional approaches. However, too little attention has been paid to the role of smart agents in improving the performance of negotiation approaches. Consequently, as it is stated earlier, Mezgebe et al. (2018) have proposed negotiation model considering smart product agents scheduled to be processed on two resource agents. The communication protocol was fully controlled by these product agents and the role of RFID technology was partly used to help detect disturbances and send back to product agents for its management. As continuation of this work, this paper has considered a full sized academic experimental platform configured with four executing resource agents and many real time events that demand more dynamic decisions; zone B of (Fig. 2). Product & resource agents are made to broadcast information among each other with complete involvement of RFID technology and PLC technology. Meanwhile, the experimental simulation scenario has been significantly improved with a greater analysis of performance criteria on higher instances.

3. THE NEGOTIATION-BASED REACTIVE CONTROL SCENARIO

As it has been emphasized in (Fig. 1), if unexpected system disturbance that has significant impact on a master production schedule (MPS) has occurred, heuristic rescheduling is expected right after the interruption to save the master schedule. The big concern at this juncture is how to make all control agents to define best decision in order to behave in a sense that the whole system stays globally sufficient for its immediate goal. To simulate this decision, a physical system of carpentry factory with four chronological work activities namely cutting (resizing), drilling, sanding, and coating is modeled based on the TRACILOGIS platform shown in (Fig. 2). The modeled physical system is composed of four intelligent machines M_1, M_2, M_3, and M_4 to execute these operations. In case of unpredictable failure of one machine, others have the capability to perform all operations.

3.1 The TRACILOGIS platform

TRACILOGIS test-bed platform lets studying different types of identification, traceability, and control (either centralized, distributed, or hybrid of the two) for products & logistic chains in wood industry. It is composed of an extensive system of networks, linking different actors of the system, be they sensors, actuators to automata or even automata to computers, RFID (Radio Frequency IDentification) sensors, PLC (Production Line Controller agents that manage all of the automaton actions of their area) etc. Additionally, it allows to assess the impact of new & smart technologies, test & demonstrate new production decision modes, and confirm running modes for production control through its four automations; *Zone-A* to *Zone-D* in (Fig. 2).

3.2 Simulated configuration of the physical system

Three product types from three customer orders Order-1, Order-2, and Order-3 are considered to be executed on the system at full batch horizon and for each order; ten intelligent products (P_i) are launched on the platform. Each product agent follows the standard routing sheet based on the MPS given in **Error! Reference source not found.**. Products are made to enter the system based on their sequential order; order-1 enters first and order-2 & order-3 follows but Order-3 succeeds order-1 at the exit of the system as the production decision has used SPT dispatching rule during the production process. In the MPS based routing sheet shown in Table 1 and (Fig. 2), products in order-3, for example, passes on M_1 for their first operation (O_1), moves to M_2 for their next operation (O_2), loops on buffer stoke zone until the products of order-1 completes their processing time in M_3, travels to M_3 for their third operation (O_3), and finally routes to M_4 for their fourth operation (O_4).

While following this route, if products expect to route without their optimal operational sequence due to many reasons (e.g., when unfortunate work-in-process pile-up between M_1 and its upstream has encountered), it will lead to high resource setup time, tardiness, and other subsequent problems. Hence, the work-in-process piled-up routing sheet is made to pursue negotiation-based reactive decision. Simulation with MATLAB is performed in order to compare this negotiation-based approach with pure reactive control approach and to pinpoint the best priority based product sequencing. Accordingly, all agents have been cooperated by computing and analyzing intention of products, step-1 in (Fig. 3). The intention of each product '*i*' is to arrive and process in each machine '*m*' and each product compute (step-2 in (Fig. 3)) its intention and broadcast to machine that it is approaching based on its arrival, process, and release times, "(1)", and to other products, step-3 in (Fig. 3).

$$v_{i(m)} = [a_i \ p_i \ r_i], \forall i = 1, 2, ..., n \quad (1)$$

where $v_{i(m)}$ is intention of product '*i*' in machine '*m*', a_i, p_i, r_i, respectively are the arrival, process, & release times of product '*i*' and '*n*' number of products in the system. Therefore, from **Error! Reference source not found.** and "(1)",

$v_{1(1)} = [5\ 2\ 7]$, $v_{1(2)} = [36.5\ 1\ 37.5]$, $v_{1(3)} = [97.5\ 4\ 101.5]$, $v_{1(4)} = [109\ 4\ 113]$, $v_{2(1)} = [5\ 2\ 7]$, $v_{2(2)} = [0\ 0\ 0]$, $v_{2(3)} = [25.5\ 4\ 29.5]$, $v_{2(4)} = [37\ 4\ 41]$, $v_{3(1)} = [5\ 2\ 7]$, $v_{3(2)} = [36.5\ 1\ 37.5]$, $v_{3(3)} = [141\ 4\ 145]$, and $v_{3(4)} = [152.5\ 4\ 156.5]$

After each product sends its intention, resources are expected to being used in order to utilize their capacity, taking the predetermined optimal capacity of resources to reduce the setup time based on the utilization model given in "(2)".

$$\text{Utilization rate} = \frac{\text{Actual process time}}{\text{Maximum processing time}} \quad (2)$$

Table 1. The MPS for three customer orders

Customer orders	Completion time (C_{im}) of each product in each order				Due date	Remark
	M_1	M_2	M_3	M_4		
Order-1	7	37.5	101.5	113	150	Ends its route
Order-2	7	0	29.5	41	78	Ends its route
Order-3	7	37.5	145	156.5	193.5	Ends its route

The values presented in Table 1 are cumulative sum of product's transportation time from machines' M_m to M_{m+1} (with 5, 29.5, 18.5, 60, 7.5, & 43.5 seconds for start→M_1, M_1→M_2, M_1→M_3, M_2→M_3, M_3→M_4, & one full loop in zone B respectively) and its processing time on machine M_m (with 2, 1, 4, & 4 seconds for M_1, M_2, M_3, & M_4 respectively).

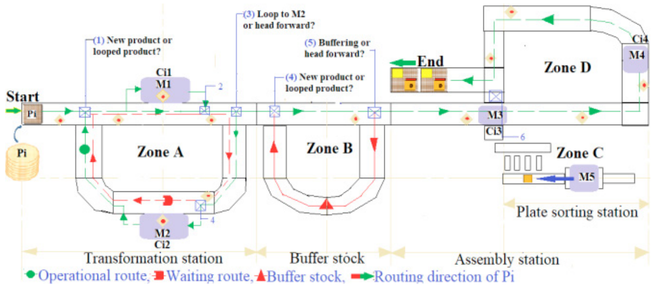

Fig. 2. The TRACILOGIS test-bed platform model

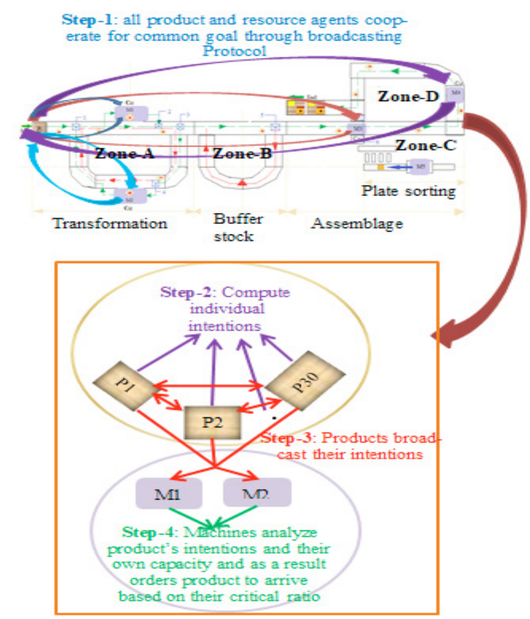

Fig. 3. Products intention versus resources efficiency

Once the utilization rate has been determined, products should keep their due date by computing their makespan and tardiness in order to complete their route before the due date. Thus, products calculate their makespan and tardiness from "(3)" and "(4)" respectively.

$$c_{im} = \sum_{i=1}^{n} \sum_{i,1}^{i,n\_i} (O_{im} + T_{im}) \;\&\; C_{max} = \max(C_1, C_2, ...C_j) \quad (3)$$

$$L_i = C_{im} - X_{im} \;\&\; Tard_i = \max(L_i, 0) \quad (4)$$

where, C_{im} is product completion time, C_{max} is the makespan, O_{im} is processing time of product '*i*' in machine '*m*', T_{im} is the transportation time of product '*i*' to next machine '*m*', X_{im} is the mean of product completion time, L_i is product lateness, and $Tard_i$ is product tardiness

To maximize utilisability, to minimize input buffer, and to minimize queuing time of remaining operations, resource agents request each product to arrive based on their critical ratio order with an intention to process a product with least critical ratio first. This makes the machine agents to understand whether product '*i*' is approaching tardy or not. Hence, each resource agent has to calculate the critical ratio (CR_i) of product '*i*' based on the model shown in "(5)". In "(5)" total routing sheet time remaining is the setup, processing, transportation, and expected queuing times of all remaining operations.

$$CR_i = \frac{\text{Due date - current time}}{\text{Total routing sheet time remaining}} \quad (5)$$

After a product *i* computes its intention and sends to all neighbor *j* products, the j^{th} products, in turn, evaluate the intention set by product '*i*' and they will accept if it doesn't affect their predetermined critical ratio or ask product '*i*' to revisit its intention, step-4 in (Fig. 3). For example, when the last product of order-2 and first product of order-1 meets in decision point '2' of (Fig. 2), the intention of product of order-2 is to succeed product of order-1 as the due date of product of order-2 is less than that of product of order-1. If not, product of order-1 will have to route a loop in the buffer zone until product of order-2 directly passes to M_3. This in turn, could delay the routing and completion time of products of order-3. Finally, products prioritization has to be validated by resources through recalculating their utilization rate for every acceptance of intention of products, step-4 of (Fig. 4).

4. ANALYSIS & MANIPULATION OF SIMULATION EXPERIMENTS

Two hundred MATLAB simulation runs have been executed for each control approaches. The pure reactive control approach was simulated considering the "*change the product intention*" routing principle such that products only have a little information about other's state, resource status, and routing. While products do not allow sending their correct intention, resources become inefficient and are led to high setup time when the products are tardy and hence the global makespan increases linearly. After this, the negotiation-based reactive control approach is simulated with "*update the product intention and routing*" principle. To compare the significance of these two control approaches, three performance measures were used and presented as follow.

The simulation results considering the product lateness (or tardiness) is illustrated in the upper part of (Fig. 4). In the negotiation-based control approach, agents have able to reduce the lateness to a minimum of 10,019 unit times in one of their simulation run but in pure reactive control approach, the minimum lateness has recorded to be 23,021 unit times. This shows that the product lateness in the routing sheet has reduced, on average, by 30.5% as a result of the environment created for the former approach. Following the minimization of product lateness, the utilization rate of resource (M_1) has also improved; lower part of (Fig. 4). On average, capacity of M_1 and M_2 is utilized 11.3% and 10.3% respectively better than the pure reactive control approach. On the other hand (Fig. 5) presents that in pure reactive control approach, once product agent has set its sequential route, it almost continue to follow this route instead of setting another optimal route that helps him minimize its makespan. But in the case of negotiation-based control approach, product agent updates its preset route to all other agents to help minimize its makespan. The maximum makespan during the former approach is exposed to be 5,022 unit times but it is reduced to 4,851 unit times following the pursuance of the second approach. This predicates that the makespan is minimized by 3.4% after employing the second approach.

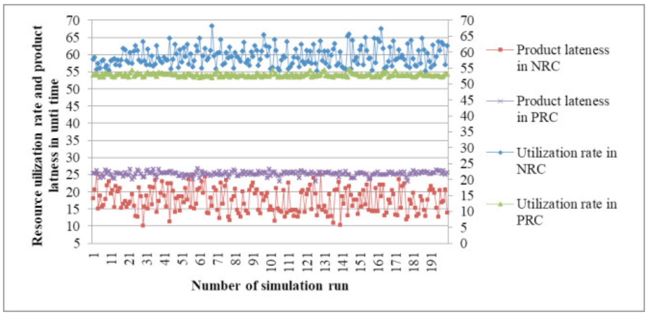

Fig. 4. Analysis of product lateness and resource utilization rate in both control approaches

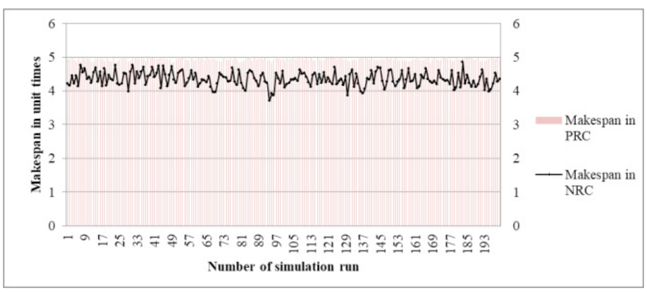

Fig. 5. The makespan analysis in both control approaches

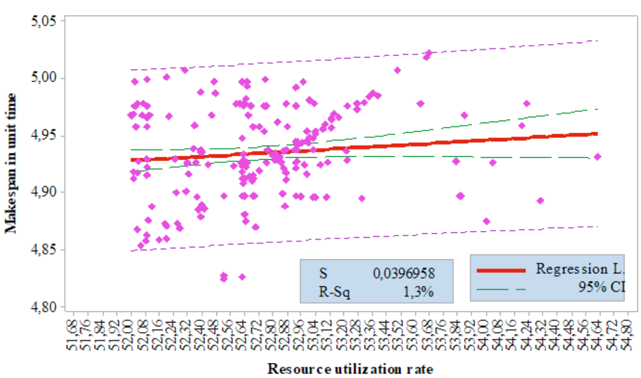

Fig. 6. Makespan versus resource utilization (M_1) in PRC

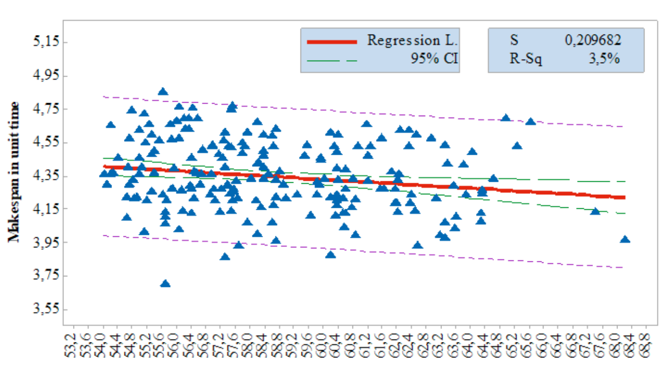

Fig. 7. Makespan versus resource utilization (M_1) in NRC

The simulation experiment has also compared two performance indicators to each other. For instance, as shown in (Fig. 6), while the resource utilization rate increases, the makespan also increases gradually. Though the machine is busy in processing the operations of predecessor products, it could not be able to minimize the makespan as successor products reach the resource without understanding its status. Hence, the successor products are obligated to wait close to the resource (excess buffer) until their processing time start on the resource. (Fig. 7) has reversed this tendency; the makespan values are shifting downward when the resource utilization increases. Statistically, (Fig. 6) illustrates that all the makespan values are closer to the fitted regression line by 1.3% (the squared or coefficient of determination, ‘R-Sq’) but in (Fig. 7), the makespan values are closer to the coefficient of regression line by 3.5%. This shows that after employing the negotiation-based control approach, all the makespan values are positioned around the regression line and consequently the routing sheet has optimized by 52.09% than following the pure reactive control approach. To recap the analysis, three of the performance indicators have shown significant advantage of negotiation based control approach in increasing adaptability and flexibility of decision entities within a disturbed industrial environment.

5. CONCLUSION AND FURTHER REMARK

This paper has presented that the role of negotiation based multi-agents system is increasing in supporting decision making capability of manufacturing entities. For instance, the simulated scenario has improved the routing sheet by minimizing the makespan by 3.4% over the pure reactive control approach. However, it has left to fully enrich the system as agents might decide alone while they are on their route. Thus, to enhance the validated results, a consensus-based distributed control system has to be explored with an objective to make agents to converge towards a predefined intention. For example, the maximum resource utilization rate obtained using the negotiation model was 68.2%. Why not more than this? To bring such advancement, agents have to continuously negotiate before they start an execution and converge to a common offer. And the design and development of this algorithm will be the continuous work of this paper.

REFERENCES

Anderson, C. and Bartholdi, J.J. (2000). Centralized versus decentralized control in manufacturing: lessons from social insects. *Complexity and complex systems in industry*, pp.92-105.

Aydogan, R., Baarslag, T., Hindriks, K.V., Jonker, C.M. and Yolum, P. (2013). Heuristic-Based Approaches for CP-Nets in Negotiation.

Blum, C. and Sampels, M. (2004). An Ant colony optimization algorithm for shop scheduling problems. *Journal of Mathematical Modelling and Algorithms*, 3(3), pp.285-308.

Botti, V. and Giret, A. (2008). *ANEMONA: A Multi-agent methodology for Holonic Manufacturing Systems*. Springer Science & Business Media

Cardin, O., Trentesaux, D., Thomas, A., Castagna, P., Berger, T. and Bril, H. (2015). Coupling predictive scheduling and reactive control in manufacturing: state of the art and future challenges. *In Service Orientation in Holonic and Multi-agent Manufacturing* (pp. 29-37). Springer International Publishing

Dimopoulos, Y. and Moraitis, P. (2006). Multi-agent coordination and cooperation through classical planning. In Intelligent Agent Technology, 2006. *IAT'06. IEEE/WIC/ACM International Conference on* (pp. 398-402). IEEE.

Farid, A. (2004). *A review of Holonic manufacturing systems literature*. University of Cambridge Institute for Manufacturing, Cambridge UK, Tech. Rep.

Herrera, C., Belmokhtar-Berraf, S., Thomas, A. and Parada, V. (2016). A Reactive decision-making approach to reduce instability in a master production schedule. *International Journal of Production Research,* 54(8), pp.2394-2404.

Holvoet, T. and Valckenaers, P. (2006). Exploiting the Environment for coordinating agent intentions. *In International Workshop on Environments for Multi-Agent Systems* (pp. 51-66). Springer Berlin Heidelberg.

Isern, D., Sánchez, D. and Moreno, A. (2011). Organizational structures supported by agent-oriented methodologies. *Journal of Systems and Software*, 84(2), pp.169-184.

Jennings, N.R., Faratin, P., Lomuscio, A.R., Parsons, S., Wooldridge, M.J. and Sierra, C. (2001). Automated negotiation: prospects, methods and challenges. *Group Decision and Negotiation,* 10(2), pp.199-215.

Koch, V., Kuge, S., Geissbauer, R. and Schrauf, S. (2014). Industry 4.0: *Opportunities and challenges of the industrial internet*. Strategy & PwC.

Kraus, S. (1997). Negotiation and cooperation in multi-agent Environments. *Artificial intelligence*, 94(1-2), pp.79-97.

Kraus, S. (2001). *Strategic negotiation in multi-agent environments*. MIT press

Leitão, P. (2009). Agent-based distributed manufacturing control: A state-of-the-art survey. *Engineering Applications of Artificial Intelligence*, 22(7), pp.979-991.

Liang, Y.C. and Smith, A.E. (2004). An Ant colony optimization algorithm for the redundancy allocation problem (RAP). *IEEE Transactions on reliability*, 53(3), pp.417-423.

Mezgebe, T. T., El Haouzi, H. B., Demesure, G., Pannequin, R., & Thomas, A. (2018). A Negotiation Scenario Using an Agent-Based Modelling Approach to Deal with Dynamic Scheduling. In Service Orientation in Holonic and Multi-Agent Manufacturing (pp. 381-391). Springer, Cham

Nagarajan, M. and Sošić, G. (2008). Game-theoretic analysis of cooperation among supply chain agents: Review and extensions. *European Journal of Operational Research*, 187(3), pp.719-745.

Pach, C., Berger, T., Sallez, Y., Bonte, T., Adam, E. and Trentesaux, D. (2014). Reactive and energy-aware scheduling of flexible manufacturing systems using potential fields. *Computers in Industry*, 65(3), pp.434-448.

Pannequin, R., & Thomas, A. (2012). Another interpretation of stigmergy for product-driven systems architecture. Journal of Intelligent Manufacturing, 23(6), 2587-2599

Rahwan, I., Ramchurn, S.D., Jennings, N.R., Mcburney, P., Parsons, S. and Sonenberg, L. (2003). Argumentation-based negotiation. The Knowledge Engineering Review, 18(4), pp.343-375.

Rosenschein, J.S. and Zlotkin, G. (1994). *Rules of encounter: designing conventions for automated negotiation among computers*. MIT press.

Saharidis, G.K., Dallery, Y. and Karaesmen, F. (2006). Centralized versus decentralized production planning. *RAIRO-Operations Research*, 40(2), pp.113-128.

Shen, W., Hao, Q., Yoon, H.J. and Norrie, D.H. (2006). Applications of agent-based systems in intelligent manufacturing: An updated review. *Advanced engineering INFORMATICS*, 20(4), pp.415-431.

Tonino, H., Bos, A., de Weerdt, M. and Witteveen, C. (2002). Plan coordination by revision in collective agent based systems. *Artificial Intelligence*, 142(2), pp.121-145.

Valckenaers, P. and Van Brussel, H. (2015). *Design for the unexpected: From Holonic manufacturing systems towards a humane mechatronics society*. Butterworth-Heinemann

Vlassis, N. (2003). *A Concise introduction to multi-agent systems and distributed AI*.

Weiss, G. ed. (1999). *Multi-agent systems: A modern approach to distributed artificial intelligence*. MIT press.

Wooldridge, M. (2009). *An introduction to multi-Aagent systems*. John Wiley & Sons.

Zambrano, G., Pach, C., Aissani, N., Berger, T. and Trentesaux, D. (2011). An approach for temporal myopia reduction in heterarchical control architectures. *In Industrial Electronics (ISIE), 2011 IEEE International Symposium on* (pp. 1767-1772). IEEE