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Using process-mining for understating the emergence of self-organizing manufacturing systems.

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Abstract: Self-organizing systems, a class of distributed systems, aim to maintain the purpose and intentions of the system regardless internal and external perturbations. These systems are composed of reconfigurable architectures and intelligent decisional entities that allow the achievement of both performance and reactivity needs. Beside other needed characteristics, such as modularity or customizability, the functioning of self-organizing systems is reliant on the degree of diagnosability during the system execution. An adequate diagnosis of the system dynamics allows the understanding the information contained and provides valuable input for the decision-making process. Process mining is a tool that permits identifying trends and patterns from event logs. This paper focuses on the use of process-mining for the diagnosis of a self-organizing manufacturing system. The approach is tested considering two self-organization rules based on the machine selection within a manufacturing environment. The approach was experimentally tested on a simulation model of a flexible manufacturing system. This exploratory research suggests that process-mining is a promising approach for the diagnosis of the behaviour of self-organizing systems.

Keywords: Process-mining, Emergence, Self-organized systems, Reactivity, FMS, Machine selection, Control

1. INTRODUCTION

Systems face the challenge of accomplishing global performance and reactiveness within highly dynamic environments. Recently, researchers and practitioners have shown an increased interest in self-organizing systems for their adaptability to uncertain events. A Self-organizing system is a class of systems able to change, spontaneously and without external intervention, the structural arrangement, the behavioural functioning and/or the dynamical progression, so the overall objectives are pursued (Leitão, Barbosa, & Trentesaux, 2012; Silva Belisario & Pierreval, 2013). The main objective of a self-organizing system is two-folded. First, it aims to guarantee a stability of the system functioning in order to mitigate the occurrence of a system interruption (Konstantopoulos & Antsaklis, 1999). Second, it intends to recover a previous functioning in the execution in order to mitigate the degradation due to perturbations. Both objectives aim to control the functioning of the system to sustain a certain level of global performance (Rooker et al. 2009). In other words, while the stability contributes to the reactivity, the recovery contributes to improving the global performance requirements.

Self-organizing systems display several operational advantages that allow them to adapt to changing condition (Barbosa & Leitao, 2010). The modularity of decisional entities, the flexibility in the architecture and customizability in the system constituent elements provide sufficient characteristics for adapting and reactive to perturbed scenarios (Jimenez, 2017). For example, concerning these advantages, these systems are able to change the structure and behaviour of the components for adopting a required architecture. Also, these are configured with artificial intelligence capabilities that control the dynamics for achieving the expected stability and recovery. For this reason, this research focuses on understating self-organizing system under normal conditions, and get insights of their response subject to environmental perturbations.

Classical self-organizing systems are based on bio-inspired (Dias- Ferreira, Ribeiro, Akillioglu, Neves, & Onori, 2016), social-inspired (Epstein, 2006), holonic (Barbosa, Leitão, Adam, & Trentesaux, 2015), or multi-agent systems (Morandini et al., 2009) paradigms. Even though these approaches feature different perspectives for the self-organizing characteristics, the global performance and reactivity requirements reached by these approaches rely partially on the diagnosability carried out during the system execution. For this paper, the term diagnosability refers to the ability to comprehend the system functioning, organizing the information into a meaningful structure and identifying significant relations oriented towards the decision-making process (definition inspired from (Cardin & Castagna, 2009; Cegarra & Hoc, 2006)).

One of the greatest challenges when diagnosing self-organizing system comes from their inherent distributed nature. In distributed systems, the purpose or objective of the system is divided between several decisional entities to improve the tolerance and responsiveness to failures

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(Trentesaux, 2009). The obstacles are that these components have limited view of the whole system and the optimal performance may be achieved only in local sub-problems rather that in the global system. Consequently, the system may not guarantee a certain level of performance and it may experience a myopic behaviour in the decision-making (Zambrano Rey, Bonte, Prabhu, & Trentesaux, 2014). In this sense, it is needed a mechanism to diagnose the dynamics of self-organizing systems with the aim of understanding the emergent behaviour resulting from local decisions, to understand how they react to internal and external perturbations, and consequently to evaluate the impact of adaptation processes on the system's global performance.

One way to tackle the stated challenges of diagnosability in self-organizing systems is using process-mining. Process-mining is a discipline that aims to discover, monitor, and improve real processes by extracting knowledge from event logs available in information systems (Van Der Aalst et al., 2012, Rozinat, Zickler, Veloso, Van der Aalst, & McMillen, 2009). From a preliminary literature review, there has been no detailed investigation into the use of process-mining as a tool for improving the diagnosability and decision-making process for self-organizing systems. From our perspective, this lack of research comes from the fact that process-mining focuses on the functioning of business or administrative processes rather than operations, such as manufacturing or logistics operations. Therefore, process-mining may be a potential mechanism that contributes to the performance and reactivity needed in self-organizing system. In this context, this paper explores the feasibility and potential benefits of process-mining within the functioning of self-organizing systems.

In this paper, it is conducted an initial evaluation of process-mining applied to self-organizing systems. This document is organized as follows. Section 2 introduces a brief explanation of process-mining and performs a preliminary review of the literature regarding the use of process-mining in self-organizing systems, or any other distributed system. Section 3 introduces the case study and present the methodology used for the evaluation. The results are presented in section 4. In the end, section 5 rounds up the paper with the conclusions of this research.

2. PROCESS-MINING FOR ANALYSING SELF-ORGANIZATION MANUFACTURING SYSTEMS

Maruster et al. (2002) define process-mining as follows: process mining is a "method for distilling a structured process description from a set of real executions". Process-mining covers various techniques to extract knowledge from event logs coming from information systems. Table 1 presents an example of event logs for a flexible manufacturing system. By using process-mining techniques, it is possible to discover issues, monitor processes, and hence, analyse and improve execution processes (Van der Aalst et al. 2011). Van der Aalst (2006) proposes three types of process-mining techniques, depending on the presence of an a-priori model: a) Process discovery, which is used to create a process model that does not exist beforehand; b) Conformance checking, which attempts to quantify the fitness between some predefined processes model and the real execution; and c) Extension results, which attempts to modify and improve an existing and known model, respectively.

Table 1 Event logs of a flexible manufacturing system

Case ID	Resource	Job	Timestamp start	Timestamp end	Operation
PTi273	M1	PTi	11/12/2017 9:39:45	11/12/2017 9:39:55	Plate Loading
PTi273	M7	PTi	11/12/2017 9:41:14	11/12/2017 9:41:34	Axis Mounting
PIi442	M7	PIi	11/12/2017 11:33:08	11/12/2017 11:33:28	Screw Mounting
PIi442	M5	PIi	11/12/2017 11:34:32	11/12/2017 11:34:37	Inspection
PIi442	M1	PIi	11/12/2017 11:34:56	11/12/2017 11:35:06	Plate Unloading
PEi412	M7	PEi	11/12/2017 11:14:14	11/12/2017 11:14:24	Axis Mounting
PTi154	M2	PTi	11/12/2017 11:17:17	11/12/2017 11:17:37	Axis Mounting
PTi154	M2	PTi	11/12/2017 8:39:36	11/12/2017 8:39:56	R Mounting
...	...	...	...	...	...

From the literature, process-mining can be applied to self-organizing systems from several perspectives (Cabac et al. 2006): a) the decision-making process, b) the internal control of the decisional entities, c) the external control of the dynamics of the system, and d) the structural/behavioural characteristics of the system. The decision-making perspective focuses on the decision models encoded in a decisional entity. The internal control perspective concerns the inner processes running within decisional entities. The external control perspective concerns the interactions among decisional entities. Last, the structural/behavioural perspective focuses on self-organizing system structures arrangement and behaviour patterns. Furthermore, Cabac, Knaak, and Moldt (2006) mentioned that "the decisional perspective is concerned with analysing the rules that a single decisional entity are based on; i.e. the question how does the component map observations to actions. In doing so, temporal aspects are often neglected; i.e. the behaviour is analysed in a certain situation without taking into account the history leading to this situation." The objective of the decisional perspective is most of the time to reconstruct the preconditions for a given action but can also detect the most frequent decisions patterns emerging during an execution. In addition, the internal control perspective focuses on the control flow of entity's behaviour viewed by a single entity type. The interactions with other entities are only taken into account by the analysed entity or entities (Denz 2014). The internal control perspective can also be used to study the behaviour in time considering only one type of entity, such as products in manufacturing systems.

In addition to these examples, there have been few attempts to analyse self-organizing systems using process-mining. For instance, Rozinat et al. (2009) used process-mining to analyse a robot soccer multi-agent system. This multi-robot system was modelled as a control architecture where multiple agents (soccer robots) coordinate the execution of different individual tactical approaches. Indeed, like soccer players, in order to achieve a common goal (e.g. win the game). In this case, process- mining was used for three different purposes with a decision perspective: discover a model for every player, compare the model found to the behaviour observed,

and extrapolate additional information. As a result, this method allowed improving the behaviour of each player in order to reach the common goal.
Cabac et al. (2006) also used process-mining for analysis, design and validation of multi-agent interactions. The self-organizing systems used in this case, called MULAN (MULti Agent Nets), is a system composed of several Petri net-based agent platforms interacting with each other Process-mining was used to analyze the interaction between each platform, using all the introduced perspectives. Another example, in a supply chain environment, process- mining was also used to create supply chain simulations in the case of various independent factories (Van Dongen, van Luin, and Verbeek 2006). The simulation model was built as a multi-agent game. At the start of a round, customers placed their orders to the factories. Each factory had until the end of the round to produce the products to satisfy demand. Herein, process-mining was used to analyze the decisions of each factory agent. Withdrawn information from the auction processes was used to determine the internal processes of each factory agent in order to predict which choice will be made in future cases (Van Dongen, Van Luin, and Verbeek 2006).

3. CASE STUDY

The benchmark proposed in Trentesaux et al. (2013) is used as a case study for this exploratory experiment. This paper applied the process-mining techniques to a simulation model of a real flexible manufacturing system (FMS). The benchmark is a FMS composed with seven workstations with a single machine each (i.e. M1, M2, M3, M4, M5, M6 and M7) placed and connected through a transportation system conveying shuttles. The system has a partial traceability system because it contains 45 nodes (From N1 to N45) as sensors of the FMS, specifically for the jobs. Some of them, called divergent nodes, are decision points where a shuttle has to decide which direction should be taken (eg., stay on a central loop or enter the waiting queue of a machine). This FMS is able to manufacture seven types of jobs, named B, E, L, T, A, I and P. Each job is composed by a specific configuration of either 4, 5 or 6 components and it is assembled in a specific sequence through diverse operations. For processing the jobs, a plate (placed onto a shuttle) enters the FMS and moves through the transportation system in order to be processed by the machines. In this case study, it is only permitted ten shuttles at the same time. Each machine can process a set of one or more operations from the job sequence (i.e. partial operation flexibility). Then, the jobs need to choose the machine of the next required operation (e.g. machine selection), and it commands the route through the divergent nodes (e.g. path selection). Figure 1 illustrates the flexible manufacturing system used.

The main goal of this experiment is to evaluate the potential benefits of process-mining in self-organizing systems. In detail, it is compared two strategies in the self-organizing systems, and these are evaluated with the process mining technique. Certainly, this proposed methodology is applicable to the traceable or partially traceable systems as it is needed the events logs from the production order execution. For the experiment, it is processed 490 jobs (i.e. 70 jobs of each type) and it starts its production at 8:00 am, called production order from now and forward. Machine 6 is not used. The releasing order into the cell is constant, and it follows the solution from a genetic algorithm. The explanation of this metaheuristic model is out of the scope of this paper. To integrate self-organisation mechanisms in the manufacturing process, it has been specified that these decisions are taken dynamically by jobs themselves. These jobs are modelled as intelligent agents for both introduced kinds of decision (machine selection and path selection). For the machine selection, each job runs an internal process to selects the next machine to address within the transportation system. This internal process is executed in each node, where the system is acknowledged of the position of the job. If the node is a divergent one, then a decision is taken by the job about the best path to reach the requested machine. In this case, it is compared two approaches for the machine selection rule, named ***potential fields and first available machine (FAM)***. While the job configured with the potential fields approach choose the subsequent machine by evaluating the availability and distance of candidate machines using a metric inspired by electromagnetic fields, the jobs configured with the FAM rule choose the closest available machine of the FMS. Further explanation of these machine selection rules can be found in Zambrano (2014).

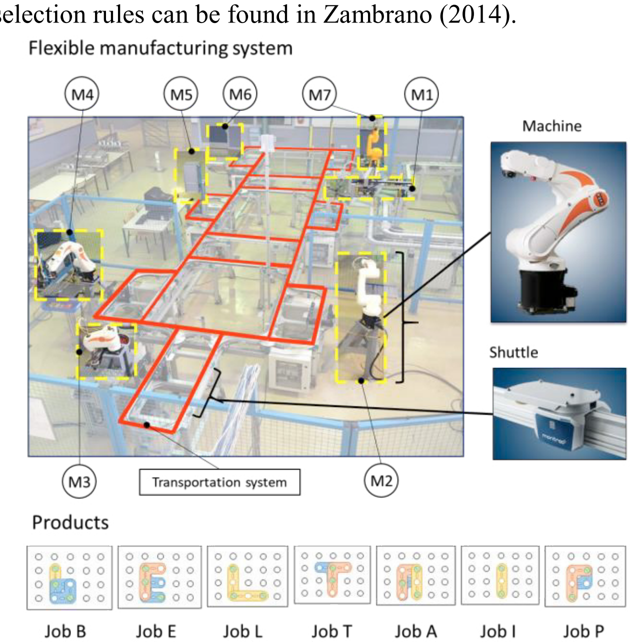

Figure 1 Benchmark of a FMS (Trentesaux et al. 2013)

The experiment conducted consider two environmental conditions, normal and abnormal, where the abnormal is associated to a perturbation occurring on Machine M2 (Breakdown) from 9:00 to 10:00 am. The experiment and the execution of scenarios were conducted in an agent-based simulation software, named NetLogo (Wilensky, 1999). Besides the simulation of the manufacturing process, the NetLogo model is programmed to print the event logs in a CSV file. The event logs used in this case study are case ID, job, Resource, Operation, Starting timestamp and Ending timestamp. An example of the events logs for this case is presented in Table 1. The event logs are introduced in a process-mining toolkit called DISCO (Günther & Rozinat, 2012). The used application for this case study is a process analysis, classified as a discovery analysis due to the absence of an a-priori model. It used an alpha algorithm in order to construct a causality from a set of sequence events. These parameters are chosen in the DISCO tool. The results are extracted from this toolkit.

4. RESULTS

As mentioned before, process-mining is used herein to understand and compare the behaviour of such self-organizing system with two machine selection rules: potential fields and first available machine (FAM), considering normal and abnormal conditions. Three different analysis are drawn from process-mining results: a) the global rule behaviour, which refers of the emergence featured for each machine selection rule; b) the machine selection patterns, which refers to the trends in the machine selection; and c) the bottleneck analysis, which refers to the identification where the process is constrained.

The following subsections show some preliminary findings in the use of process mining from our experiments. The scope of this study was limited to evaluate the potential of this technique in the execution of systems. Therefore, it is clear that there is future research to follow in order to determine the point of application of this technique and how the diagnosis of self-organizing manufacturing systems could be improved in order to predict the emergence of these kind of systems.

4.1 Global rule behaviour

For the potential fields approach (See figure 2a), the effectiveness of this rule is easily identified since the number of jobs selecting machine M2 is higher than its redundant machine M7 (which is located farther away), comparing the normal conditions with the perturbed scenario (179 served by M2 vs 151 served by M7). On the contrary, for the FAM approach (see figure 2b), even though M7 serves more jobs during the perturbation, the mean waiting times at M7 are higher because jobs are blocked, and need to wait other processes to continue on the transportation system.

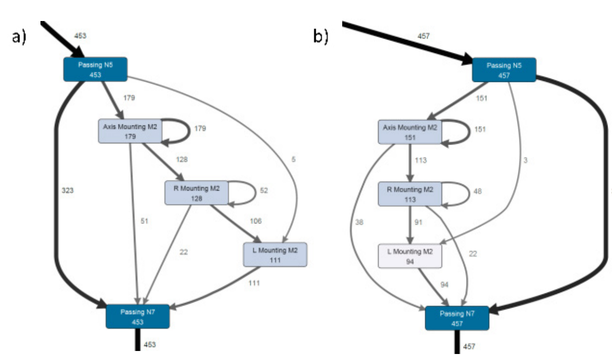

Figure 2 Process flow for machine 2 with a) Potential fields and b) First available machine (FAM).

An additional analysis for the potential fields rule was made aiming to find a trend in the self-organizing systems´ behaviour. Figure 3 shows the histograms of the completion time of each job in the production order (e.g. 490 jobs) for potential fields under normal and abnormal conditions. For normal conditions, the production order has a makespan of 15418 seconds, the completion time of the jobs is 5.141 minutes and the standard deviation of 1.254. For the abnormal conditions, the production order has a makespan of 16842 seconds, the completion time of the jobs is 5.623 minutes and the standard deviation of 1.877. Nevertheless, it seems that a certain pattern can be found in the execution under normal and abnormal conditions. Regardless the perturbation event in the abnormal scenario, both histograms have similar patterns around the mean. Nevertheless, the abnormal conditions present a set of jobs that exceeded the expected completion time (Figure 3 in bottom histogram). Although these results give insights of the effectiveness given by the machine selection rule (e.g, potential fields), further research should be undertaken to investigate the effectiveness capability of this rule in self-organizing systems. Indeed, this is a premature conclusion and it requires further statistical analysis. However, it is interesting to explore this information aiming to foresee, a certain behaviour of self-organizing systems.

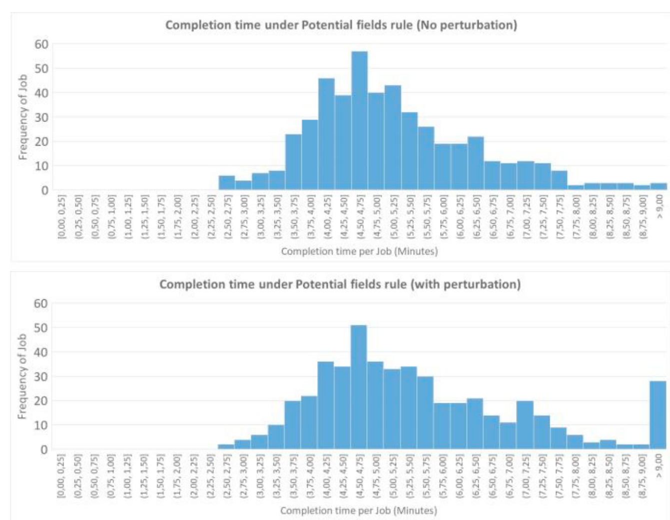

Figure 3 Histogram of the completion time of each job (Normal and abnormal conditions).

4.2 Machine selection patterns

Since each job chooses a machine one by one according to their process plans (sequence of operations), jobs of the same type can have different machine sequences. As a result of the process-mining analysis, machine selection variants can be found. A process variant is a specific sequence, like a trace through the process, from start to end. It is important to state that a decision is updated at each divergent node, where the product gathers information about the manufacturing current state. For the potential fields approach, 186 variants were found for the case with no perturbation and 224 variants were found for the case with perturbation, meaning that the potential fields rule diversifies the machine sequences as a response to the perturbed scenario. Table 2 shows the first 20 variants, which represent around 50% of the jobs sequence. For instance, job type "T" follow variants 1, 2, 6, 8 and 9 while job type "A" follow variants 7 and 17 for most of them.

This is an interesting result because it helps to find sequence patterns for jobs and hence either use such information for predicting jobs' behaviour or integrating more intelligence into the job, to deal with perturbations. The same information was obtained for the perturbed case and since the number of variants increase, the first 20 variants only depict the behaviour of 40% of jobs.

The last column in Table 2 refers to the number of times a job passed through a decisional node, i.e. points of decision. This number of steps in the process depends not only on the job's production plan (number of machines it requires), but also on the trajectories chosen. For instance, for jobs type "E", variants 3 offers only 25 points of decision whereas variant 10 offers 26 and variant 14 offers 31 points of decision. Henceforth, variants 10 and 14 comprise more transportation times and possibly more revisions of decisions made, due to machine state changes (i.e. if at one divergent node a job decides to go to a machine x and at the next divergent node the machine is busy, the job might change its decision for a less busy machine).

Table 2 Resulted variants from the process mining

Variant	Mean (min)	Job	Quantity of Jobs	Number of Steps
Variant 1	3,69	Pti	17	23
		Ppi	14	
Variant 2	4,73	Pti	8	29
		Ppi	11	
Variant 3	4,13	Pei	15	25
Variant 4	4,52	Pai	14	26
Variant 5	4,66	Pbi	14	26
Variant 6	4,02	Pti	9	23
		Ppi	5	
Variant 7	4,25	Pai	13	26
Variant 8	5,36	Ppi	8	37
		Pti	4	
Variant 9	4,97	Ppi	8	25
		Pti	3	
Variant 10	4,76	Pei	11	26
Variant 11	5,61	Pli	10	37
Variant 12	3,55	Pli	9	23
Variant 13	4,25	Pli	9	23
Variant 14	5,15	Pei	9	31
Variant 15	6,57	Pli	9	40
Variant 16	4,76	Pli	8	26
Variant 17	5,87	Pai	8	40
Variant 18	5,74	Pbi	8	40
Variant 19	4,27	Pli	7	26
Variant 20	6,19	Pli	6	45

Instead, for the FAM rule, 488 variants were found for the non-perturbed case and 490 variants for the perturbed case. Since the production order has 490 products, this number of variants means that each product has a unique sequence. By making and in-depth analysis of such variants, it can be found that jobs tend to turn around the system (central loop) trying to find free machines and hence their transportation time increase, and their decisions change constantly at each point of decision. Variants are mostly different because they take into account all the decision nodes jobs passed through. As a conclusion, it is harder to find patterns for the FAM rule than for the PF rule since its behaviour is more unstable. The least number of steps is 32 and the highest number of steps is 234, confirming the changeable behaviour of jobs.

4.3 Bottleneck analysis

Figure 4 shows the bottlenecks found for the potential fields rule (first row) and FAM (second row). The bottlenecks are found from the average waiting time between two nodes. For the potential fields rule, bottlenecks are found for those machines that lack redundancy, such as loading/unloading (located at nodes N2, N29 in our model) and inspection (M5). On the contrary, for the FAM rule, given the unstable decision-making, bottlenecks are also found at the divergent nodes where jobs need to decide either one route or another to the to the subsequent machine (nodes N45, N4, N17).

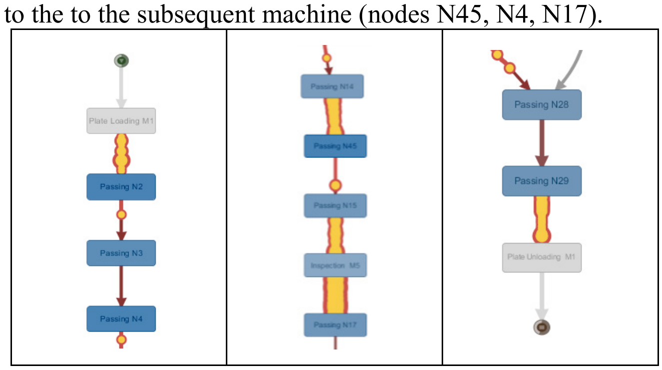

Figure 4 Visualization of the flow of the production order under normal and abnormal conditions

Figure 5 shows a simulation screenshot for the FAM rule, focused on the bottleneck problem at node N2 just before machine M2. Since the third job made its decision at N2 when M2 was available, it blocks the main path from the transportation system.

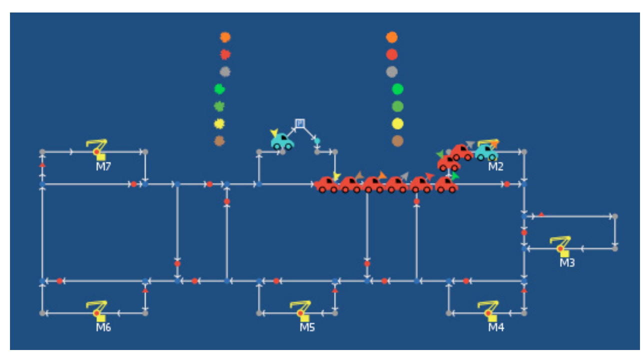

Figure 5 Simulation model with FAM as machine selection.

6. CONCLUSIONS

This paper presents the application of process-mining for the analyzing and diagnosing of self-organizing systems. The case studied is composed of intelligent decisional jobs, which are in charge of selecting the machines they require to fulfil their production plans. Two machine selection rules were analyzed, the potential fields approach and the first available machine rule. A production order was launched and it was extracted the event logs after the execution. These event logs were used to make a process-mining analysis. . After the regular descriptive statistics analysis, the most interesting conclusion comes from the pattern analysis. It shows that it might be easier to predict the behaviour of self-organizing systems based on potential fields rather than using the first available machine. By doing so, it will be possible to estimate production indicators such as completion times before or during execution. Until now, this type of predictions has not been explored for self-organizing manufacturing systems.

Another conclusion is derived from the capability of finding patterns. It is possible to use these patterns to enhance the job intelligence, for instance by giving different but effective variants to the job it helps its decision making, particularly under perturbations. Consequently, the job can be guided and the system will be more predictable. And last, bottleneck analysis can also be helpful to include a featured rule that will balance workload by avoiding bottlenecks (machine or path). A promising research perspective of this exploratory research concerns the online inclusion of the process mining technique. We believe that an online diagnosis of the self-organizing systems would improve the engineering of the emergence of the systems and will permit to react smoothly and efficiently to perturbation events.

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