On the Suitability of AI for Service-based Adaptive Supply Chains in Smart Manufacturing

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***Abstract*—Recent years witnessed a growing interest in the employment of intelligent techniques for the management of manufacturing processes in smart manufacturing. These processes may include tens of resources distributed among several different companies composing the supply chain. The status of the different resources evolves over time in terms of cost, quality, and probability of break/unavailability, thus requiring the process to be adaptive and resilient to disruptions. Due to the high number of involved resources, making decisions manually soon become unfeasible, thus requiring automated techniques to solve the problem. In this paper, we discuss the potential and limitations of automated reasoning techniques for making modern supply chains adaptive and resilient by relying on the information provided by resources through their APIs.**

***Index Terms*—Industrial API, Smart manufacturing, Automated reasoning, Planning, Markov Decision Processes**

I. Introduction

The concept of *smart manufacturing*, embodies a vision of industrial processes where computing devices are integrated in most of manufacturing steps. In particular, industrial processes are supposed to be fully (or mostly) automated, adaptive to changes, flexible, evolvable, resilient to errors and attentive to the more knowledgeable operators' skills and needs. Of the utmost importance in this context are *adaptivity*, i.e., the ability of the system to adapt to certain conditions, e.g., a rescheduling of the production process, and *resilience*, i.e., the capacity to continue the work despite disruptions as the breakdown of a machine. These two objectives are particularly challenging due to the dynamism and uncertainty of manufacturing environments. In factories, for example, machines are subject to wear and may provide unpredictable results.

Processes must not be considered isolated though. They instead involve several companies along complex supply chains [1]. Such a network of players co-operates together to accomplish multiple production goals. They consist of loosely coupled entities, and their organizational structure is adapted dynamically according to the tasks to be performed [2].

In such supply chains, the total amount of manufacturing resources is huge. Also, they belong to several different categories including software systems, machines, robots, and human workers. Each resource provides a set of functionalities and has its own characteristics, e.g., quality, speed, costs, and probability of break. Noteworthy, the very same functionality can be offered by different resources, optionally from different categories (e.g., painting a part can be done either by a machine or by a human), and the execution of a multi-party process requires an accurate selection of resources in order to be completed in the most convenient way. Such a selection though, cannot be considered static as the conditions of resources change over time, as well as needs and (potentially conflicting) performance measures. Additionally, non-trivial constraints between resources may exist, making the overall task of choosing actions and resources difficult to be performed manually. The employment of Artificial Intelligence (AI) techniques can simplify the task. In particular, specific automated reasoning techniques though have their own expressiveness that, in turn, influences the computational costs.

In this paper, we discuss how automated reasoning techniques, indeed a specific type of AI, can be used to provide adaptivity and resilience to multi-party processes in smart manufacturing. To this aim, as proposed in [3], we model the manufacturing resources as components of a Service Oriented Architecture (SOA): each resource involved in the manufacturing process is a service accessible through an *Industrial Application Programming Interface (API)*. Industrial APIs provide many features like accessing the selected services, enabling quick integration, monitoring the behavior and status information, and invoking commands.

II. Adaptive supply chains

Supply Chain Design (SCD) [4] involves many conflicting aspects. Among them, we found facility location planning, allocation of customers to distribution centers or factories, and suppliers selection. Also, recovery plans are a fundamental strategy in order to overcome disruption events caused, for instance, by broken machines or context change. Various recovery strategies are provided in the literature [5], including relational strategies such as supply chain collaboration, communication and information sharing [6]. In this sense, it is essential for industrial partnerships to collaborate to quickly recover from disruption. Moreover, a flexible supply chain network structure is found appropriate for formulating appropriate disruption risk recovery strategies [7].

In general, the common goal is the development of the *triple-A* supply chain, which consists of the simultaneous implementation of three different ideas, i.e., *agility* – responding to short-term changes in demand or supply quickly, *adaptability* – adjusting supply chain design to accommodate market changes, and *alignment* – establishing incentives for

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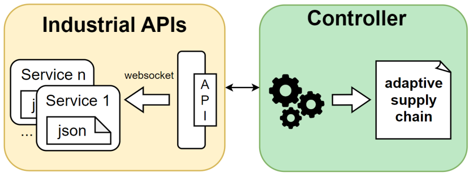

Fig. 1. Service-based adaptive framework

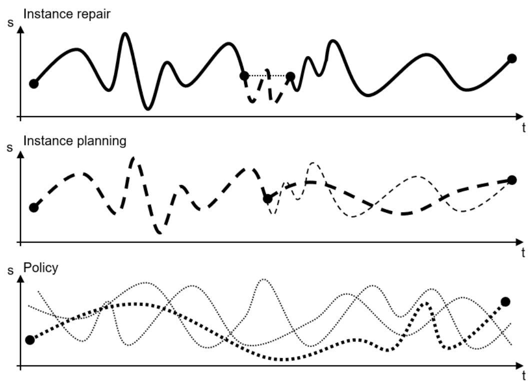

Fig. 2. Schematizing adaptive strategies.

partners to improve performance of the entire chain [8]. We enrich such definition by including *resilience*, as the ability to react to disruptions along the chain. Adaptivity and, more in general, the flexibility of processes is discussed in [9], but the focus is generally on processes, with no specific reference to industrial processes and supply chains.

All adaptive approaches found in the literature can be modeled as black boxes (*controller*s) taking as input the specification of the involved resources (in our case a set of services) and the final target (in our case a manufacturing goal) and providing as output an adaptive process (see Fig. 1). A conceptual classification of the possible alternatives can be defined by considering the different options for inputs and outputs. Concerning the input, we can distinguish between the deterministic and non-deterministic (or probabilistic) behaviors of manufacturing resources, and between fully specified and under-specified manufacturing goal.

Fig. 2 shows an intuitive representation of the three possible strategies generated as output. For each of them, the horizontal axis represents the evolution over time, whereas the vertical axis is an intuitive representation of the overall state of the resources (a tuple) in some numeric form. Each action performed in a supply chain is actually a couple $< a, r >$ where a is an action and r is the resource executing the action. The chosen sequence of actions and manufacturing resources change the state of the resources from an initial state, to a final one representing the end of the manufacturing process and possibly fulfilling the manufacturing goal(s). In the following the three different types of strategies are described.

Instance repair. The supply chain process is precisely defined. If an unexpected exception happens (e.g., a machine breaks), automated reasoning is employed to restore the state of resources to the expected one. Adaptivity is applied locally, but the overall forthcoming process remains unchanged. In Fig. 2, the process model is represented using a solid line, whereas adaptation is represented using a dashed line.

Instance planning. Every time that a new process instance is needed, automated reasoning is applied taking as input the most recent information about resources and producing as output an entire process model. If, at a certain point of the execution, something (e.g., a broken resource) prevents the plan to be completed, automated reasoning is applied again. In Fig. 2, the part of the process that cannot be executed is represented through a thin dashed line, whereas the thick dashed line represents the process actually executed.

Policy-based. Automated reasoning is employed to obtain a policy, i.e., a function that for each state proposes the next action. Differently from the *instance planning* case, here if something unexpected happens, there is no need to reapply planning, as all the possibilities have been already computed. In Fig. 2, all the possible legal executions of the process are represented through dashed lines. Among these, according to the state of the different resources, a specific one (represented as a thick dashed line) is chosen.

III. Case study and experimental framework

In order to show the suitability of a supply chain adaptive approach, we apply it to the challenging case of integrated circuits (chip) manufacturing[1], analyzing the efficiency, adaptivity, and limitations of the different approaches. Although semiconductor design activities are concentrated in specific regions of the USA, as well as in Europe and Japan, semiconductor manufacturing is more widely dispersed. The industries that provide manufacturing inputs and purchase finished semiconductor products are often dominated by large, multinational organizations [10]. In addition, as witnessed by the recent evolution of international political affairs, this production is strongly influenced by relationships among countries, which may produce unpredictable effects on the supply chain.

We implemented an experimental framework composed of a prototype platform to manage the manufacturing resources (services) maintained by the Industrial APIs and a controller representing the black box generating the adaptive supply chain (see Fig. 1). On the one hand, the Industrial APIs platform relies a middleware that allows the management of all the services involved in the manufacturing process. It is composed of a WebSocket server and an HTTP server. Particularly, it connects to the services via WebSockets, having a separate communication channel with each one, and exposes APIs to manage HTTP requests. The defined APIs allow retrieving both the specification and the current state of the services and request the execution of a task to be performed by a service. Each resource is described as a JSON file which is used by the middleware to “build” the service. Such a file contains specific elements: *(i)* an *id* to

[1]Cf. https://www.screen.co.jp/spe/en/process and https://www.asml.com/en/news/stories/2021/semiconductor-manufacturing-process-steps

specify the identifier of the service, e.g., name of the resource, *(ii)* some *attributes* that contain the static characteristics of the service, e.g., actions and costs, and *(iii)* some *features* that contains the dynamic characteristics of the service, e.g., status, breaking and quality condition. On the other hand, the controller encloses an adaptive supply chain approach which orchestrate the manufacturing resources depending on the employed methodology. In the preliminary experiments we applied three different approaches: *(i)* an instance planning approach based on classical planning, *(ii)* a stochastic policy approach employing Markov Decision Processes (MDPs), and *(iii)* a stochastic constraint-based policy approach employing DECLARE formulas (i.e., LTL_f [11]) and MDPs.

IV. Preliminary results and conclusions

We conducted initial experiments applying adaptive approaches to the case study of chip manufacturing chain and we measured the space-time complexity as the number of services (i.e., manufacturing resources) involved increases.

In approaches based on automated planning, increasing the number of services does not significantly change time and memory consumption as Planning solvers employ well-known heuristics that efficiently derive solutions. However, this approach does not consider stochasticity, which refers to the probability of a certain machine failing, whereas stochastic approaches represent and address this aspect.

On the other hand, memory consumption and execution time of the stochastic policy approaches increases exponentially, as the number of services increases. This is due to the cartesian product operation performed among the manufacturing services to represent the entire supply chain environment. Additionally, the stochastic constraint-based policy approach requires more time and memory with respect to the stochastic policy approach, mainly because of logical constraints.

Even though more efficient approaches are generally preferred, other factors may come into play in the manufacturing context. Depending on the circumstances, the expressiveness of the modeling language may allow to express complex aspects of the smart manufacturing scenarios. Both the proposed stochastic approaches, despite being much slower than classical planning, have great expressive power as they capture the stochastic behaviours in the manufacturing domains.

All the considered approaches require to express constraints concerning the step to be performed during the supply chain process execution. Depending on the chosen approach, such constraints are modeled in different ways. The planning-based approach requires a very precise specification of actions, which is fundamental for generating, given a goal, a process to be followed. However, it allows to model the involved products and demi-products by monitoring the production progress. In contrast, the approach based on stochastic policy requires a full definition of the manufacturing process (defined as an automata). This is different in its extension which employs LTL_f. Here, the process is loosely specified by using constraints.

Another complex aspect to be analyzed, is how to model constraints between resources available to execute specific tasks (e.g., if resource A is used, then resource B cannot be used). In the case of planning, this type of constraint can be modeled with conditional effects which, however, have consequences in the computation costs. It is not easy to model this behavior instead in the stochastic policy approaches because the defined goal only relies on manufacturing tasks and does not consider the resources employed.

In this paper, we introduced a batch production case study. In this sense, we study the adaptivity by taking into consideration the fact that a specific task of the supply chain production is executed on a batch, thus if a decision is taken at the beginning of a task, it is maintained until the end of it. Such an approach influences adaptivity by discarding the possibility of adapting the production inside a specific batch and considering only the adaptivity at the end of a task.

During the initial experiments, we only considered automated reasoning, excluding machine learning (reinforcement learning in particular) techniques. Machine learning does not require any manual modeling effort, but it usually requires datasets to be trained, which are difficult to obtain in the smart manufacturing scenario, especially at a supply chain scale.

Also, we did not considered approaches from classical numerical optimization techniques. These techniques are available in the form of very fast implementations. The main drawback is that modeling must be done in the form of equations, which are more complex to compose and validate with respect to formalisms employed in automated reasoning.

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References

[1] N. Bicocchi, G. Cabri, F. Mandreoli, and M. Mecella, "Dynamic digital factories for agile supply chains: An architectural approach," *Journal of Industrial Information Integration*, 2019.

[2] H. Stadtler, "Supply chain management: An overview," *Supply chain management and advanced planning*, 2015.

[3] T. Catarci, D. Firmani, F. Leotta, F. Mandreoli, M. Mecella, and F. Sapio, "A conceptual architecture and model for smart manufacturing relying on service-based digital twins," in *ICWS*. IEEE, 2019.

[4] D. Ivanov *et al.*, "Literature review on disruption recovery in the supply chain," *International Journal of Production Research*, 2017.

[5] S. K. Paul and P. Chowdhury, "Strategies for managing the impacts of disruptions during covid-19: an example of toilet paper," *Global Journal of Flexible Systems Management*, 2020.

[6] H. Y. Chen *et al.*, "Building resilience and managing post-disruption supply chain recovery: Lessons from the information and communication technology industry," *IJIM*, 2019.

[7] R. Dubey *et al.*, "The design of a responsive sustainable supply chain network under uncertainty," *The International Journal of Advanced Manufacturing Technology*, 2015.

[8] H. L. Lee *et al.*, "The triple-a supply chain," *Harvard business review*, 2004.

[9] M. Reichert and B. Weber, *Enabling flexibility in process-aware information systems: challenges, methods, technologies*. Springer, 2012.

[10] J. T. Macher, D. C. Mowery, and T. S. Simcoe, "e-business and disintegration of the semiconductor industry value chain," *Industry and Innovation*, 2002.

[11] G. De Giacomo and M. Favorito, "Compositional Approach to Translate LTLf/LDLf into Deterministic Finite Automata," in *ICAPS*, 2021.