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Article *in* Procedia CIRP · September 2020

DOI: 10.1016/j.procir.2020.04.151

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 93 (2020) 32–37

www.elsevier.com/locate/procedia

53rd CIRP Conference on Manufacturing Systems

An Industry 4.0 framework for tooling production using metal additive manufacturing-based first-time-right smart manufacturing system

Mandaná Moshiri[a,*], Amal Charles[b], Ahmed Elkaseer[b,c], Steffen Scholz[b,d], Sankhya Mohanty[a], Guido Tosello[a]

[a]Department of Mechanical Engineering, Technical University of Denmark, Building 427, Produktionstorvet, 5 DK-2800 Kgs. Lyngby, Denmark
[b]Institute for Automation and Applied Informatics, Karlsruhe Institute of Technology, 76344 Eggenstein-Leopoldshafen, Germany
[c]Faculty of Engineering, Port Said University, Port Fuad 42526, Egypt
[d]Karlsruhe Nano Micro Facility, Hermann-von-Helmholtz-Platz 1, 76344 Eggenstein-Leopoldshafen, Germany

* Corresponding author. Tel.: +45-52211838. *E-mail address:* manmos@mek.dtu.dk

Abstract

This paper presents a concept for an integrated process chain for tooling production based on metal additive manufacturing. The proposed approach aims at taking advantage of a fully digitized production line, describing the main steps for the synergetic integration of the manufacturing assets. The production line entails digital infrastructure that collects and elaborate data from various monitoring sensors to execute corrective actions and continuously optimize the process. This line will bring breakthrough benefits, like flexibility and full traceability. Also challenges, as change management in the industry, skills gap, the requirement of new business models and product re-design have been addressed.

Keywords: Smart manufacturing, Industry 4.0, Additive Manufacturing, Automation, Tooling

1. Introduction

Metal Additive Manufacturing (MAM) is a group of digital production technologies that involve manufacturing the product layer-by-layer using metallic materials. In one of the most industrially-relevant MAM processes, known as laser powder-bed fusion, a thin layer of metallic powder is iteratively spread over a building platform and processed with a laser (of appropriate wavelength, power, frequency and pulse duration). The laser scans over the layer according to the CAD design of the product being manufactured in order to selectively melt corresponding areas of the powder bed [1]. Such a process allows unparalleled design and material freedom, which opens the possibility for new product-functionality and performances [2,3]. The main current applications of MAM involve biomedical [4], aviation and aerospace [5], automotive [6] industry and tooling production [7]. The production of mould components for injection moulding exemplifies one of the most successful implementations of MAM for tooling production. In particular, MAM enables introduction of conformal cooling channels (curved conduits inside the insert) into the new design of mould inserts. These conformal channels promote a more efficient cooling of the plastic injected inside the mould, thereby decrease the manufacturing cycle time, improving the thermal management (dissipation) of the process, and enhancing the quality of the plastic product [8–10]. Although there have been some attempts to utilise MAM for tooling, there have been no detailed study on incorporating MAM into a full production line for first-time-right (FTR) tooling manufacturing. In this context, the scope of this paper is to present an original concept of a smart and holistic production system, incorporating elements of Industry 4.0, for the manufacture of mould tool components by using MAM technologies. In the proposed production line, every step will be fully monitored to collect manufacturing data in order to recognise responses, control their performance through

10.1016/j.procir.2020.04.151

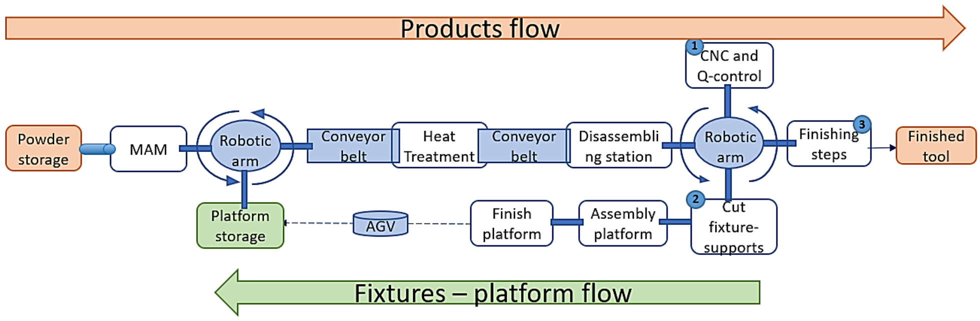

Figure 1 Manufacturing process chain for tooling production.

continuous process optimisation, and ensure full traceability of the products and the equipment used. The integrated manufacturing process chain is presented in subsequent sections of this paper with an initial focus on the aspects that make it "smart" and digital. Then, the advantages and expected challenges of such a production line are explained along with other key aspects, while highlighting the research gaps to be addressed for reaching the final objective.

2. Integrated manufacturing process chain

2.1. Production flow

Figure 1 illustrates the layout and the workflow of the proposed production line for tooling manufacturing, wherein a single independent production module/unit is defined for a hybrid chain. The layout contains all the required steps to fully produce a complete tool, making it an independent production module. Further, the module contains both additive and subtractive technologies and is designed for manufacturing companies that can work with products of small lot size, down to a one of part production. The integrated process chain starts with the design of the components using CAD software, in combination with advanced tools like topology optimisation and generative design, to simultaneously take advantage of the MAM increased design freedom as well as ensure the optimum performance of the final product. A topology optimisation tool would ensure equal (or even better performance) while optimising other design parameters, for example reducing the weight [11,12]. Next, the performance of the optimised part under "in-service" conditions has to be simulated to ensure that the functional requirements are satisfied. Simulations of the manufacturing process are also conducted to predict eventual issues during production of the optimised part, and adopt necessary preventive/corrective measures [13,14]. In current digital production lines, the simulation step has already become important, with the significance set to increase along with the advancement of faster and more reliable algorithms. The digital and Industry 4.0 integrated nature of the process chain will further promote the significance of simulations by collecting manufacturing data and component-related information via monitoring. The monitoring information would provide the real boundary/environmental/process conditions necessary for the simulations, while the manufacturing data will provide the initial validations for the simulation results. Subsequently, machine learning algorithms can identify the key performance indicators correlating the manufacturing data variables, monitoring data variables and simulated outputs of interest (corresponding to specifications of the product). This would create a knowledge feedback-loop whereby the digital production system would continuously learn from the previous process instances to better simulate the successive instances [15,16]. For products with a larger lot size, the response models created via the machine learning algorithms can increasingly substitute simulations in the daily production workflow within the integrated manufacturing process chain, while simulations will still play a major role in pre-production stage. However, for small lot size production, simulations will play an active role during production stage with response models from machine learning algorithms solely being used for feedback process control. It is worth emphasizing that to achieve this goal, and other objectives later presented in this paper, application of machine learning will be essential.

The manufacturing process proposed for the MAM is Laser Powder Bed Fusion (LPBF). Metal powder from storage, e.g. a silo, is directly fed into the machine´s dispenser through a pipe. Then, using optimal processing parameters, the MAM machine produce a component near-net-shape to the final product. Any residual unused powder in contact with the part is removed by a robotic arm that also removes the build plate on which the part is produced, and put it on a conveyer belt. This will bring the platform and the part inside a furnace for heat treatment, for the relief of residual stresses resulting from prior MAM process and bring the metal alloy to its optimal mechanical properties.

Since the component has already a geometry close to the final one (near-net-shape) it will not require a great amount of material removal. However, considering the current limitations of LPBF technologies regarding part´s precision, accuracy and surface quality [17–20], some extra post-processes are necessary to meet the requirements of the final application. 5-axis CNC operations together with some other finishing operations, e.g. wire-EDM and polishing, are included depending on the final application of the tool [21]. For simplifying these post-processing operations, the part is printed directly on top of a designated fixture. To make this manufacturing line fully integrated, behaving as a unique system, compatible fixtures assembled in a frame can be integrated building platform of the MAM machine [22,23]. Then, another conveyor belt after the furnace will move the part to the disassembling station, where a robotic arm separates the different products. Integrated functional features, such as the fixtures integrated into the MAM building platform, help reducing the lead-time of the production by eliminating further processing steps. This would also lead to a simplification of the overall manufacturing line, the reduction of manufacturing errors and more energy efficiency [24]. In the disassembly process, each disassembled fixture is picked by a rotating robot that will bring it to the final processing steps. The next step for finishing is inside a CNC workstation that can include equipment for quality control of the product (e.g. photogrammetry or CMM probes). The quality control step can be performed before the CNC operation, to check the quality of the MAM product, and after the operation, to ensure that the desired tolerances are achieved. Similarly, these controls can be performed also on the drilling/milling bits used for machining, to check their wear and to send an alert when it needs replacing. The robot then transfers the part to the second station, where the component and the fixture are separated, so the first can proceed to the third station, where some final post-processes are conducted and the product is ready to use. As formerly mentioned, example of final finishing processes can be EDM or polishing, depending on the tool´s purpose. Meanwhile, the fixture is moved to an assembly station, to be reused for the building platform for MAM, after any necessary post-processing (e.g. grinding) and then stored (moved by an AGV system) close to the MAM machine. The robot in charge of the powder removal and the platform movement can pick it and fix it inside the machine to start the process again. As presented also in Figure 1, it is possible to recognise two main flows: a product process flow and a platform/fixtures flow.

2.2. Digital process chain

What makes this proposed production line “smart” and “integrated” is how the process is monitored and data are collected and handled. In Figure 2 a data infrastructure is proposed: each and every step of the manufacturing line need to be equipped with sensors to fully monitor the process in real-time. In particular, real-time monitoring is used to instantaneously capture the conditions of the working environment for further data processing and feedback (correction) and continuous optimisation of the manufacturing process. The corrective measures can be performed autonomously via software algorithms or manually using human machine interactions (HMI). Data acquisition in real-time monitoring can be implemented using, for example, smart sensors and thermal cameras in order to inspect the quality of the printed products in-line. In our case, the physical system is AM (L-PBF), and thus the physical features of an L-PBF process such as oxygen content in the build chamber, temperature of the powder, attributes of laser (power, focal distance, spot size, frequency, etc.), the melt pool radiation, optical quality of the powder spreading on the platform and power consumption could be monitored [25,26].

All of these data is then filtered and processed, to select only the ones that represent the product quality fingerprint, and so moved to the third level of the infrastructure. Here all the processed data is collected, interpreted, analysed and correlated to the information coming from the pre-manufacturing steps (design and simulation) and post-manufacturing (tool application, maintenance and end life). This helps to identify how to optimise each step of the full life cycle of the tool. The third layer is the one that gets connected to the rest of the company´s data infrastructure and backbone, where key information is saved and data from the rest of the company´s departments are connected, such as the production scheduling and warehouse planning. This system will ensure a total horizontal and vertical integration of the whole industry, in accordance with Industry 4.0 requirements [27].

The expected outcome of real-time monitoring is to be able to recognise manufacturing issues and to enable the feedback system to address them, thus improving the precision of the process or even avoiding errors in the next fabrication trials [28,29]. In particular, by analysing the monitoring data and identifying the trends, it is possible, as mentioned, to optimise the process itself. When sufficient amount of data is collected, trends can be elaborated to predict process evolution. By implementing these information into statistical modelling approaches such as regression or through more advance AI and machine learning algorithms, it would be possible to first analyse patterns and the effects of various sensor data on the final quality of the produced part, e.g. dimensional accuracy [28], generated surface quality [30] as well as on system wide performance indicators such as cycle time or throughput [29], thereby allowing the creation of a process fingerprint [30]. Establishing a process fingerprint is vital in increasing knowledge on a process which would in turn allow the user to precisely control and tailor process parameters according to the required quality. The proposed digital process chain is designed to create a continuous learning process that would allow the process to optimise itself, with a concurrent feedback loop between real-time-control sensors and actuators implemented in the manufacturing chain. Again, these corrective action can be conducted without direct human intervention, thanks to the correlation created between process signatures and product´s quality and performance [31–33]. Optimising the process would allow in this sense a FTR process chain, by correcting real time eventual issues in the process, a reduction of the lead-time, by optimising the process itself, and ensuring always the optimal product quality and functionality, especially considering the high costs related to tooling [34]. Other important aspects coming from the monitoring of the process are related to the safety of the people in the industrial environment. This is especially true given the fact that all the equipment are always kept under control, not only the product that is undergoing the manufacturing process and thus incidents in production environment will be reduced [35]. From an ecological point of view, the data collected would also include energy, water, material and other resources consumption for each machines and the process optimisation procedures would include also decreasing these consumptions to minimize the environmental impact [24,36,37].

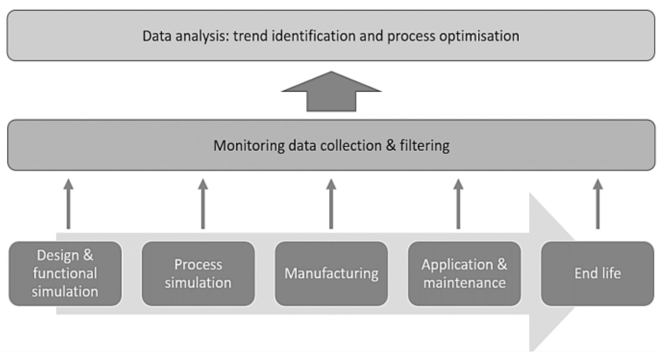

Figure 2 Data infrastructure for the global integrated digital process chain

One can argue that the smart production line so developed will produce what are defined as “smart products”. These are products that can be identified at any time (through for example QR codes, radio-frequency identification (RFID) or near field communication (NFC) by integrating apposite chips into the products [38,39]. This helps recognize the status of the part, its manufacturing process and performances during its lifecycle “in-service” or maintenance. All information regarding the tool life and end life would be recorded in their identifiable code, and this further information would allow for continuous learning about the parts´ functionalities and thus to improve its next generation while also generating data that can be used for conducting life-cycle assessment of products [40].

3. Advantages and challenges

The manufacturing line presented, as a modular independent cell that considers holistically the entire production chain for tooling in a digital and integrated manner, will have many advantages but also will pose challenges during implementation.

3.1. Advantages

Most of the advantages has been already presented above, but it is worth adding that, especially thanks to the integrated MAM system, this process chain will ensure full flexibility. This is intended as the system must be able to adapt to new and innovative production requests. However, since it is completely digitally controlled, it would require a different type of machine´s re-programming, but the equipment and the digital backbone would be already prepared to face new demands, behaving as a Flexible Manufacturing System (FMS) [41,42]. Apart from the flexibility there is also the responsiveness of the system, defined as its capability to react quickly to change. This advantage is very important today and it will become even more important in the future considering the high speed of growth of the economy and the increase of competitiveness represented by the newly developing markets [35,43,44].

A modular system that is fully digitalized also presents the possibility to easily decentralise production in locations closer to the customers or to the materials suppliers, where it is more convenient, while maintaining the centralised control of the production remotely from the headquarters [45,46]. On the other hand, the structure and the monitoring system of the line will guarantee full traceability of products and tools used for the manufacturing (e.g. fixtures, drill bits, building platform) and will be capable to capable of visualising the full life cycle. This would generate an holistic view of the process that would allow the management to take informed decisions when necessary This represents one of the main pillars of the Industry 4.0, regarding the Internet of Things (IoT) [47–49]. The high level of automation of the line will increase the robustness and the reliability of the process, improving the repeatability of the production, since the experience and the capabilities of the users will not influence the results of the products [50,51].

3.2. Challenges

At the same time, various challenges on the adaptation of an integrated production line need to be faced. The challenges mostly depend on the research gap in some of the main fields, for example process monitoring and product quality correlation, cloud computing, big data management (essential to handle the massive amount of data coming from a fully monitored process chain), and data interpretation. The last one in particular, with the integration of artificial intelligence and machine learning analytics make possible to create a self-optimising process chain and creating a feedback loop on the part quality [33,40,52,53]. Coming from this IT backbone, aspects like cybersecurity need to be faced to avoid any leaks of confidential and sensitive information [35,47]. Process simulation and innovative design, also need to be explored and improved further for actual industrial adoption. Other challenges involve the change of the human role in the process chain. Though Industry 4.0 principles envision the role of a human being to remain at the centre of future manufacturing scenarios, it will transform from the direct operation of the machine to remotely programming and controlling the full chain [34,54]. Traditional manufacturing companies with ageing populations in their workforce will need to develop strategies to deal with this type of role change by developing programmes for its employees to develop the new skill sets and raise awareness in topics, like deep simulation and coding experience [47,55]. A great amount of time need also to be devoted to change management, to make sure that the company´s environment would be ready to the change in terms of resources and of mindset. Mindset especially represents a key aspect of the adoption of a process chain aligned with Industry 4.0 concepts, since the lack of preparation and education activity can lead to a complete failure of the system, even if it is perfectly functioning from an equipment point of view, if the people are not ready to face the change [37,49]. People’s trust will play a major role in the success of implementation of a fully digital system. Especially since the nature of work changes, it is important to underline that such a system does not want to eliminate the direct role of humans, but it wants to instead change its role to a more efficient, productive and safe one, but it requires readiness of learning new skills and acceptance of the change. A challenge is also the lack of shared list of clear requirements that are necessary for an Industry 4.0 frameworks, even if this gap is getting filled in the recent years in literature [27,34,40,47,56,57]. How to face the change management will depend mostly on the reality of the industry (number of employees, level of digitisation, etc.) but investments in education and training is fundamental.

4. Discussion

One of the most important aspect in the new production chain in accordance with Industry 4.0 concepts is that it looks in a holistic way at the entire process as a unique entity: it must become an independent, organic modular system behaving as a single unit, to ensure a flexible manufacturing line. In this way, it is possible to be always fully aware that any change at any step will generate a modification in the other step of the process, and if the process is already controlled globally, the impact of these changes can be precisely measured and predicted to not create any waste or issues [48,58,29,59,60]. To achieve this vision, the compatibility and open but secured machine to machine communication for all the manufacturing assets and with reliable IT infrastructure must be ensured. An open- communication protocol will be necessary, like OPC UA, with machines that are open platforms, which allows full sharing of data, as well as user-friendly Human-Machine Interaction (HMI) interfaces [61–63]. Open communication and trust cannot refer to machine and equipment only, but also inside the company across departments: considering the increase of complexity and the diversification of skills required in the new manufacturing system, totally open communication with robust and reliable methodologies to share confidential information real time will be essential. The equipment between each other need to be compatible through the use of matching devices, like the platform-fixture system above presented. The overall manufacturing system and planning, especially in a large production framework, where multiple modules are necessary, and/or for industries working with batch size of one, needs to be carefully prepared and controlled with a robust and appropriate Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) capable of handling machines coming from different suppliers and various products. The increased focus on open communication, planning management and monitoring data analytics open up also the requirements of strong and robust data infrastructure inside the company, to store safely and share fast information, reacting promptly to any circumstances [64,65].

Regarding benefits coming from an integrated line manufacturing smart product, a direct reduction of costs cannot be expected, because of the expensive initial investment of equipment and IT infrastructure. The major benefits would be reduction of lead time and scraps, thanks to the reduction of manual intervention required, and the FTR management of the process, where potential issues are either predicted through simulation or machine learning, based on previous experiences, or identified in time to be corrected through the monitoring, together with preventive maintenance of tools and equipment. This in turns will bring eventual cost savings [34,40,66–69].

The topic of the change of human role has already been presented, but another observation is important to be discussed: not only it changes the worker´s role in the production line, but also leadership approach need to change. This is necessary to face digital evolution, the speed and flexibility requirements. Considering the global decentralisation of production using facilities that are remotely controlled, the leadership needs to be capable of controlling and managing production sites in an agile manner, while also facing changes in time zones and cultural background which require great flexibility [70,71].

The new central role of human, as robot controller and collaborator, it is a topic of great interest today in research not just in production disciplined but also in psychology and humanities, and on the side it represents also a promising field to open up new job opportunities for people with body handicap and disabilities, considering the reduction of user´s capacity required directly on the production line [72,73].

4. Conclusion

This paper has presented the concept of a smart, integrated and modular production system, designed for a hybrid process chain aiming to manufacture tooling in small lot sizes, that is with the context of industry 4.0. Several different causes of reflections have been discussed with a comprehensive list of advantages and challenges that need to be faced. The main benefits for companies in starting such a change can be summarised as follow:

- Full monitoring of the system to early identify issues to be handled, creating the fundaments for FTR production.
- The data collected from the process help gain consequent knowledge about the process which in turn can facilitate automatic feedback loops for process optimisation to be integrated in the future.
- Total traceability of products and tools used for manufacturing ensures fully understanding the effect of the manufacturing choice in the full life cycle of the AM product, also by identifying product’s fingerprints.
- By the analysis of the data regarding consumptions the process can be optimised to reduce them, to make it more environmentally friendly.
- Safer work environment were all the machinery and equipment is constantly under controlled.
- Scalable and flexible modular setup, to be quickly reactive to changes in production demands.

The integration of such a manufacturing system is disruptive compared to the current solutions, since it take a holistic look at the overall process chain. It must cover the entire process chain to get the full benefits, not just sections of it. The integration in a company must start with education campaigns to create the fundamental knowledge and understanding of the effects of it, together with change management on all levels, to ensure the right mindset when the 4th Industrial revolution gets fully underway. The digital transformation will affect the whole aspect and every sector of the organisation and for these reason new business models need to be introduced to handle it.

Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement N 721383.

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