The Paradigm of Pit - Stop Manufacturing

Tullio A. M. Tolio(✉) and Maria Chiara Magnanini

Department of Mechanical Engineering, Politecnico di Milano, Milan, Italy
tullio.tolio@polimi.it

Abstract. The context in which manufacturing companies are operating is more and more dynamic. Technological and digital innovations are continuously pushing manufacturing systems to change and adapt to new conditions. Therefore, traditional planning strategies tend to be inadequate because both the context and short - term targets are continuously changing. Indeed, one of the goals of manufacturing companies is to keep manufacturing systems efficiently running, and reduce and control the impact of disruptive events, that may originate from different sources, not always known or well defined. In order to do so, manufacturing systems should be kept relatively close to the current optimal condition, while, at the same time, taking into account information about future possible events, which may require new optimal conditions. In fact, the reaction time to the change must be short, in order to remain competitive in the market. In addition companies to be competitive should lead the introduction of changes therefore they have to be both reactive and proactive. From this analysis, the new paradigm of 'pit - stop manufacturing' is introduced, in which the overall goal is to dynamically keep the manufacturing system close to an improvement trajectory, instead of statically optimizing the system. It is shown how the 'pit - stop manufacturing' deals with various aspects of current manufacturing systems, therefore providing novel research questions and challenges.

Keywords: Manufacturing systems · Industry 4.0 · Control · Variability

1 Introduction

The context in which manufacturing companies are operating is more and more dynamic. Technological and digital innovations are continuously pushing manufacturing systems to change and adapt to always new conditions, in order to remain competitive [1–3]. Indeed, manufacturing systems can be seen as racing cars: in car races, though the overall goal is to be as fast as possible, the winning team is the one capable of mastering a strategic approach and use and minimize the impact of pit - stops during the race, by grounding on team cooperation, advanced technological solutions and information exploitation. Similarly, in manufacturing systems, the ability to timely deliver the desired quantities of products that are conforming to the customer expectations, strongly depends on how the manufacturing system is capable to deal with unpredicted events such as machine failures, delays, lack of material [4, 17, 21].

Strategies for manufacturing system improvement involve decisions at different levels having impact on different time horizons. For example, if a machine breaks down, short term production planning should adapt immediately, while maintenance

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should focus on the reduction of the repair time, in order to bring back the system to its full operational mode. On a medium term, increasing the reliability of the machine, by means of technological actions on the machine, may entail specific investments. Alternatively, the implementation of advanced maintenance policies, such as condition-based maintenance or predictive maintenance could be considered. This last option however requires additional information coming from data sources such as sensors. Therefore, decisions should be taken on the redesign of the sensory networks (i.e.: how many sensors should be installed? What is the acquisition frequency? How much data should be stored? [16]) However, by the time the decision has been taken, the context could have already changed, therefore the optimal decision needs to be continuously redesigned.

1.1 Why 'Pit - Stop Manufacturing'

In order to answer to the situation presented above, a new paradigm is introduced, 'pit - stop manufacturing'. Pit - stop manufacturing aims at considering manufacturing systems as continuously changing and evolving objects, for which optimal targets change accordingly. Therefore, the overall goal becomes to be able to react to unpredicted and disruptive events or to take disruptive decisions by acting on different decision levels and exploiting innovative technologies, novel modeling techniques and advanced digital tools:

- On the *short term*, keep the system running, by performing the required actions in the best possible way;
- On the *medium term*, develop control strategies to minimize the impact of disruptive events and stoppages on the system;
- On the *long term*, understand and translate into decisions the information about the changing context in order to proactively change and remain competitive.

Indeed, this resembles what happens for racing cars. People involved on the routine operations, such as pilots, mechanics, telemetrists in the control room, should be well prepared and highly skilled to perform their tasks at best. In fact, in the end they are the ones performing the concrete job that allows the system to keep on running. Then, the off-line efforts should be on the optimization of these operations, by providing the best possible conditions to operate.

Therefore, manufacturing systems should be characterized by *agility* and *mutability*. On the one hand, *agility* represents the ability to act quickly and easily, both mentally and physically. Therefore, agile manufacturing systems are characterized by short reaction time to disruptions [21], as well as a good control structure. On the other hand, *mutability* represents the ability to change. For manufacturing systems, *mutability* can be considered the ability to adapt to new and changing situations, by having the intuition about what to do even if it had not been done before.

Agility and *mutability* enlarge the concepts of flexibility and reconfigurability by including control actions. In fact, a manufacturing system can be flexible, but until the flexibility is not used properly, it cannot be considered agile. Similarly reconfigurability allows the system to change but only when system design and redesign is available mutability can be attained.

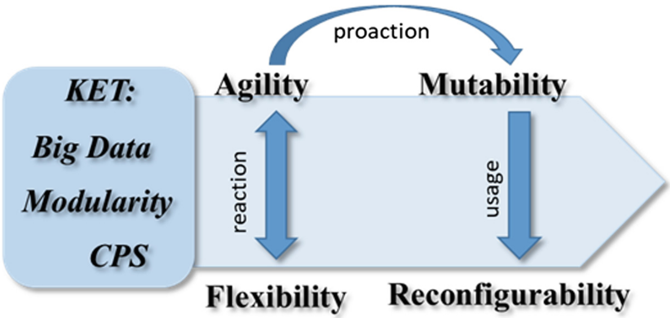

Fig. 1. Graphical representation of the key drivers for manufacturing systems in pit - stop manufacturing

1.2 Agility by Learning and Mutability by Modeling

Increasing the ability of being agile can be attained by practicing more and more when doing something. This means that, grounding on the experience and a solid control design, agility is reached by reiteratively learning how to perform the same action better and better. Indeed, data-driven techniques such as neural networks, reinforcement learning, genetic algorithms consists in learning from a defined data set how to optimally perform an action chosen in a predefined solution space [5]. The more data is available, the more the network can be easily trained to do what it is designed for. Moreover, the more the network is trained, the more it learns how to perform better its task. For instance, neural networks for image recognition after a preliminary training phase, they become quite efficient at recognizing predefined features in pictures. However, if a picture with a new feature is presented, the neural network assigns that feature to the most similar one among the set which is already known. The only way to have a correct identification is to train the neural network again by adding to the solution space the new feature. This happens because data-driven methodologies work well when the solution space is already known. By grounding on available data and available feedback about implemented actions, data-driven methodologies are capable to efficiently identify the best action in the known solution space.

However, when dealing with continuously changing conditions, it may happen that a decision has to be taken, in a new situation, for which no data is available [1]. This means that the problem moves out of the known solution space, for which the behavior of the variables involved in the decision has not been registered yet, and therefore there are not known feedbacks. As explained above, this is a fair common situation in in manufacturing systems, that are in the need to proactively change in order to remain competitive.

Hence, abstraction becomes a key factor when looking for the ability to change and adapt. In fact, models can support this situation, because they provide decisional support by formalizing existing knowledge in structures that are valid even out of the validation space. Indeed, model-based methods allow what-if analysis, as well as evaluation of situations which have never been observed in practice. Therefore, the use of models to proactively take tactical and strategical decisions represents a key characteristics of competitive manufacturing systems. Obviously, developing a model, such as a performance evaluation model of manufacturing systems, or a process control model, requires some efforts. Nevertheless, the main advantage is represented by the fact that, if the model has been well-developed, can give suggestions even out of the validation space, i.e. it is general.

1.3 Factors Considered by Pit - Stop Manufacturing

In the following, three factors that are relevant for the definition of pit - stop manufacturing strategies are presented.

1.3.1 Variability as a Central Issue

Manufacturing systems are characterized by intrinsic variability. Variability comes from different sources at different levels of the system [1, 31]. Therefore, it has an impact on different time horizons. If variability did not exist, the management of manufacturing systems would have been based on *plan*, rather than *control*. With *plan*, we mean the timed set of actions that are decided in advance in order to make the system operating, whereas with *control*, we mean the set of actions that need to be done based on some system condition in order to keep the system operating.

Variability cannot be completely deleted from manufacturing systems. Therefore, the goal is to reduce it as much as possible the variability, and to find the best strategies to cope with it.

1.3.2 Information Uncertainty

Information is not always certain. On the contrary, in most of the cases information is available with some level of uncertainty. When information comes from data sources as sensors, the efforts can be put in determining which piece of information is the most relevant one for the considered problem [8]. For instance, when dealing with the definition of maintenance strategies [32], precise information about the degradation of machines could be useful. On the other hand, other types of information do exist and play a relevant role in the overall manufacturing strategy, such as non-structured information about the changing context, weak signals from situations that require intuition in order to be understood, expertise and previous knowledge.

1.3.3 The Role of Humans

Manufacturing systems without people is still a quite un-realistic situation. Indeed, even if manufacturing systems are more and more automated, and capable of self-managing, i.e. self-detection and solving of failures, the probability of occurrence of unpredicted events remains always relatively high, due to the variability descending by the physics of the system. Therefore, though humans might represent a relevant source of randomness within the system, they are capable, if well - trained, to react, and to solve, issues that have not been completely identified, or that they have never happened before [1].

1.4 A Real Case from an Italian SME

In the following, a real case from an Italian SME is presented. Indeed, it is a representative case for manufacturing analysis, and the factors presented above can be noticed. Therefore, it serves as example for the validity of the paradigm of pit - stop manufacturing, since all considerations made above do apply to it.

Cosberg SpA is an Italian company leader in the automation sector. Cosberg makes assembly machines and assembly systems to automate the production of a great variety of products ranging from furniture fittings, to braking –systems for cars and motorcycles, to gears for wrist-watches, and more. More than 50% of the turnover of the company comes from export all over the world, warranting unique solutions and a tailor-made product for each customer.

The collaboration between the company and customers is very strong, and often they develop together strategies for the plant improvement. Therefore, usually Cosberg operates on ‘brown-field design’. Once the manufacturing line has been designed, there is a continuous process of optimization of the current line configuration with respect to its efficiency (reduction of time losses due to maintenance, reduction of set-up time for product changes, increase of product quality by selective inspection, root-cause analysis for most frequent failures) where Cosberg supports the customer, and operators are actively part of the improvement plan by suggesting actions. At the same time, reconfiguration actions are planned, tested and then implemented on the customer’s line.

In fact, the manufacturing line is continuously evolving. For instance, the manufacturing line in Fig. 3, designed for the assembly of drawer slides of ready-to-assembly kitchen drawers depicted in Fig. 2, used to have hydro - pneumatic actuators, well known for being reliable but slow.

Fig. 2. Drawer slide for ready-to-assembly kitchen furniture

Therefore, the management of the operating line has been optimized taking into account the current cycle time. At the same time Cosberg and the customer jointly worked on the implementation of electrical actuators, that allow a better control as well as a shorter cycle time than the hydro-pneumatic ones. Indeed, the optimization that had been carried out for the previous line configuration had to be reviewed, in order to consider new – and better – performance goals.

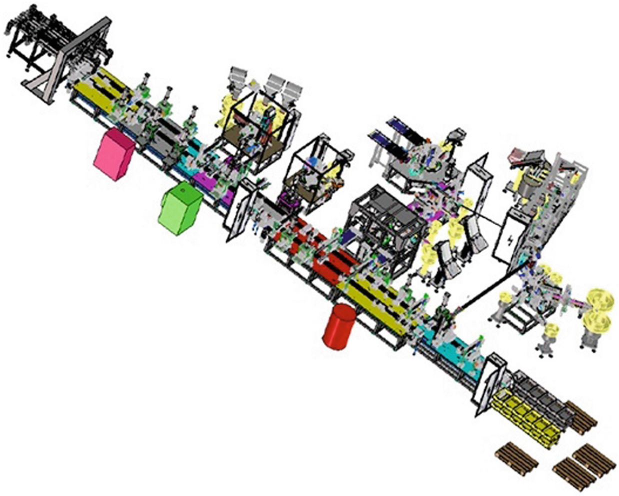

Fig. 3. Drawer slides manufacturing line as example of modular automated line provided by Cosberg

2 Challenges for Research Guidelines

2.1 Design of Manufacturing Systems

Traditionally, the design of manufacturing systems includes a set of decisions involving the elements of a manufacturing system, such as layout, machines, buffers, handling systems [15, 24]. Now, an additional element should be considered: sensors and data management. The data acquisition and management can be seen as 'a system within the system'. Its design involves questions similar to the design of a traditional manufacturing system: how many sensors? Which layout? How much storage capacity [34]? Indeed, the data management system has a direct influence on the uncertainty of the gathered information.

Moreover, the design of manufacturing systems cannot avoid to take into account considerations about the control of manufacturing systems. Not only manufacturing systems should be *flexible*, but also *agile*. Similarly, the design of manufacturing systems should take into account its necessary and unavoidable evolution and requirements to adapt to new situations [22] and therefore be *mutable*.

2.2 Ramp - Up Management

In a continuously changing context, the ramp-up of a manufacturing system should be as short as possible. Ramp-up represents a challenge for manufacturing companies because they have to deal with disruptions coming from various and unknown sources [7]. Indeed, after a change, the manufacturing system is not well-known and therefore optimization is done with respect to partial information rather than complete knowledge or sufficient data [33]. Therefore during this phase, the problem becomes to prioritize certain actions to maximize the production gains, and trying to reduce and control the variability coming from different sources. Effective strategies combine proactive and reactive actions: proactive strategy includes the anticipation of potential problems during the design phase, reactive strategy includes the ramp-up management by data gathering, bottleneck identification and analysis, system modeling and improvement.

2.3 Integrated Control Policies of Logistics, Maintenance and Quality

Quality, maintenance and production planning strongly interact and jointly determine those aspects of a company's success that are related to production quality, i.e. the company's ability to timely deliver the desired quantities of products that are conforming to the customer expectations, while keeping resource utilization to a minimum level [4]. What are the relevant information needed to take integrated decisions? For instance, both maintenance and quality policies are based on the identification of process degradation patterns, and therefore on the same set of data. Current performance evaluation models are capable to deal with logistics, maintenance and quality. The design of control policies, however, should be directly integrated within the design of the manufacturing system [18, 29], so that *agility* exploits system flexibility to its full potential.

2.4 Robust Model - Based Strategies

Dealing with model - based strategies implies the estimation of model parameters from real data. However, data might be insufficient, especially in the ramp-up phase, or completely absent. Moreover, models may consider restrictive assumptions. In order to implement model-based strategies in reality, robustness should be investigated and analyzed, with respect to the uncertainty of the information [8]. Indeed, if there is no awareness of uncertainty, control strategies may be useless or even counterproductive [9]. Robustness helps also when dealing with variability: if a control strategy is robust with respect to variability of system conditions, not only agility has been pursued, but also mutability.

2.5 Key Enabling Technologies (KET)

The following Key Enabling Technologies (KET) allow a successful development of the afore-listed research challenges in the framework of pit-stop manufacturing. They represent existing technologies that still have a consistent margin of improvement and advancement.

2.5.1 Big Data

Data come from different sources in great amount. For instance, data are not only measures, but also images, or sounds. Data can be clustered according to classification, see for instance the 3 V's model [2]. However, what is the value of the data? In order to define the value, we have to go through the identification of the meaning of the data, and then of the information [19, 27]. Interpretation plays a relevant role. Therefore, a relevant question when dealing with Big Data is whether it is possible to formalize the interpretation with the goal of an effective extraction of knowledge from the data. Indeed, Big Data are necessary for data-driven techniques that prove to be useful when aiming at agility, and also the knowledge extraction becomes essential when aiming at mutability.

2.5.2 Modularity

Modularity is the degree to which a system's components may be separated and recombined, often with the benefit of variety in use. Modularity is useful at all levels in manufacturing systems: in product design, modularity allows an effective and sustainable management of the product lifecycle [10, 11]; in manufacturing system design [23, 30], it supports easier configuration and reconfiguration decisions [20], hence leading to the agility of reacting to disruptive events. Moreover, modularity is directly linked to the development and use of models, and therefore to aim at mutability.

2.5.3 Cyber - Physical Systems

Cyber - Physical Production Systems (CPPS), rely on the latest, and the foreseeable further developments of computer science, information and communication technologies on one hand, and of manufacturing science and technology [6]. Information coming from different sources at different levels are used to close the control loop and take decisions on different time horizons [25, 26]. Indeed, manufacturing systems should be kept as close as possible to an operational trajectory. Therefore, the architecture of the control system [28], that starts at physical level up to the system level, should be coherent to the decisions that are going to be taken and the information flow that is relevant for the control loop.

3 Examples from Ongoing Projects

In the following, three examples are presented in which considerations presented above for pit-stop manufacturing do apply. The three projects have different background and come from different scenes: the first one is a European project focused on zero-defect manufacturing solutions for manufacturing systems, the second one is a huge European project focusing on the overall supply chain of semiconductors, and the third one is an Italian initiative for Industry4.0 that has put the basis for the paradigm of pit-stop manufacturing.

3.1 ForZDM: Integrated Zero - Defect Manufacturing Solution for High Value Multi-stage Manufacturing Systems

The H2020 ForZDM project "Integrated Zero - Defect Manufacturing Solution for High Value Adding Multi-stage Manufacturing Systems" was launched to propose a new production quality system specifically targeted to small lot, large variant productions, subject to frequent reconfigurations [12]. The key architecture of the system proposed in the project is represented in Fig. 4. At lower level, a multi-sensor data gathering system is implemented, enabling to collect process variables, part quality, machine state, and part tracking information as well as codified and un-codified human feedback, through intuitive and user-friendly Human-Machine Interfaces (HMIs). This heterogeneous data set is collected and organized into a data management platform, that prepares data for higher level analyses. At middle layer, a set of data-analytics methods and tools are implemented, targeted to the identification of (i) correlations among the observed heterogeneous variables, (ii) correlations among different system stages, and (iii) non-ideal part variation patterns along the system stages. These models can be used to design specific model-based control systems to be implemented at shop floor levels. Moreover, at higher level, an analytic system-level model is implemented, with the goal to identify priorities of intervention, dynamic bottlenecks, and to verify that local improvement actions that are detrimental for the overall production quality performance are avoided. Within the ForZDM project, this architecture has been being developed, tested and validated in three complex application domains, dealing with the production of engine shafts in the aeronautics industry, the production of axles in the railway industry, and the production of micro-catheters in the medical technology industry.

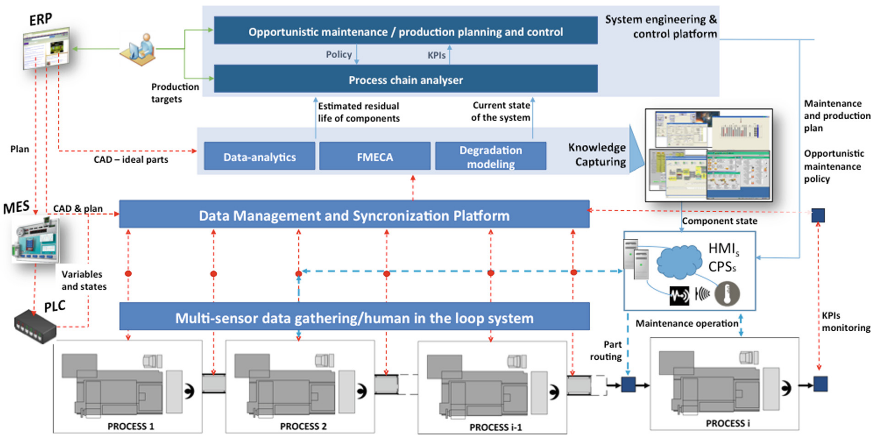

Fig. 4. Reference architecture for short - run production quality improvement proposed within the ForZDM EU project

3.2 Productive4.0: ECSEL Project

The semiconductor sector is undergoing one of the fastest market growths. Demand is increasing and market forecasts are optimistic. New markets are emerging and product portfolios are broadening significantly. Dynamic supply chains are developing with increasing number of customers, products, suppliers and manufacturing partnerships. Up to now due to modeling complexity and computation time constraints, disjoint systems are used for local supply chain control and optimization. For efficient control, these complex semiconductor supply chains require a global approach for simulation and optimization. In the ECSEL project Productive4.0, novel model aggregation approaches are introduced by means of innovative hierarchical modeling concepts. Bosch Semiconductor provides one of the use-cases. The overall goal in the Bosch use-case is the coupling of disaggregated analytical and simulation models to systematically improve overall model validity [13]. This requires a deep analysis of which data are available and significant at which level (Production Unit, Plant and Supply Chain levels). Moreover, it means investigating how data and information should pass from one level to another in order to bring value to the overall control model. Indeed, the model-based approach has been chosen by the partners in order to develop a general digitalization strategy that can adapt to changing conditions (Fig. 5).

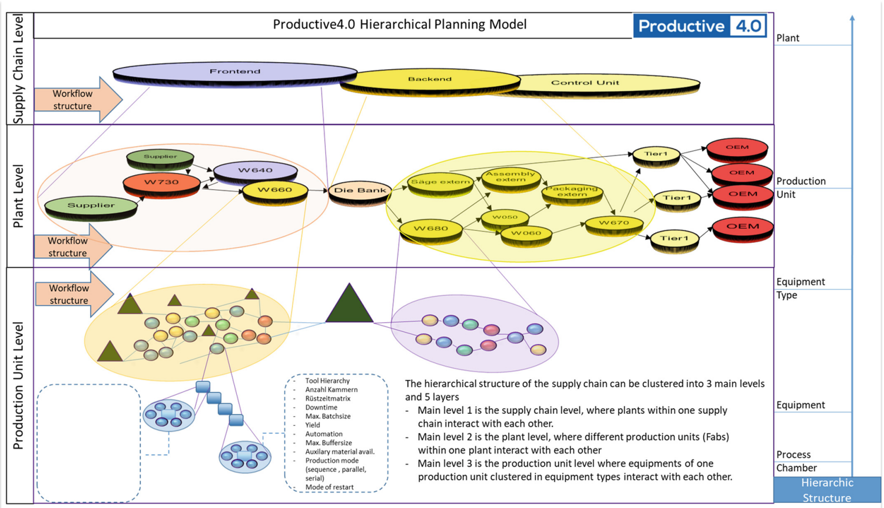

Fig. 5. Hierarchical architecture of the productive4.0 planning model.

3.3 The Italian Initiative: Lighthouse Plants

A Lighthouse Plant (LHP) is an infrastructure that aims at creating a reference production plant, owned by a company and operating in a stable industrial environment, based on key enabling technologies whose benefit was previously demonstrated (e.g. in Lab-scale or Industrial-scale pilot plants). The aim of the LHP is twofold: on the one hand, to demonstrate on a long-term basis novel technologies in operation, thus supporting the continuous uptake by industry; on the other hand, to trigger the development of industrial research and innovation activities to continuously improve manufacturing solutions according to the progress of technology [14].

LHPs are conceived as evolving systems and are realized ex-novo or based on an existing plant deeply revisited, where collaborative research and innovation, partially funded by public institutions, is carried out by the owner of the plant together with universities, research centers, and technology providers. The results of research and innovation activities are meant to be readily integrated into the plant.

The LHPs concept as presented in the previous section has been defined by Italian Cluster Intelligent Factories (CFI) to further boost the National Plan Enterprise 4.0 designed by the Ministry of Economic Development in Italy (MISE) in 2017. This plan included incentives for super- and hyper - depreciation as a way to support the implementation of advanced technologies in Italian manufacturing companies (Fig. 6).

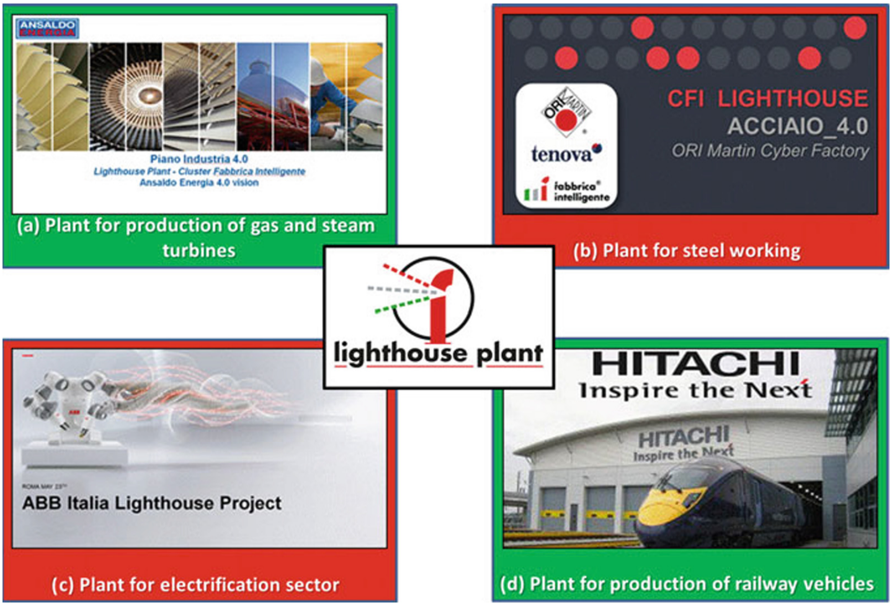

Fig. 6. Lighthouse plants approved by MISE: (a) Ansaldo Energia, (b) ORI Martin and Tenova, (c) ABB, (d) Hitachi

4 Conclusion

This work introduces a novel paradigm for manufacturing, named pit-stop manufacturing. Pit-stop manufacturing sees manufacturing systems as continuously changing and evolving objects. The reasons for the evolution are manifold: on the one hand, manufacturing systems are pushed to continuously proactively improve in order to remain competitive, on the other hand disruptive events may happen that force the manufacturing system to adapt. Therefore, control should be included into the design and management of manufacturing systems as capability to be considered for an effective manufacturing strategy. Two characteristics are defined as relevant for pit-stop manufacturing: agility and mutability, where the first one represents the ability to act quickly and easily, and the second one represents the ability to evolve and to adapt to new and changing situations.

Model - based strategies are presented as the right approach to address the evaluation of situations out of the existing solution space, rather than data-driven methodologies that perform well for given conditions. Indeed, the factors having an impact on the definition of such strategies are represented by variability, uncertainty in information and the relevant role of human.

Research challenges and relative Key Enabling Technologies are provided, and research guidelines depicted with respect to the proposed paradigm of pit-stop manufacturing. Some examples from on-going projects illustrating the main points of pit-stop manufacturing show the validity of the proposed paradigm, that aims at representing a novel approach for solid and successful manufacturing strategies.

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References

1. Gershwin, S.B.: The future of manufacturing systems engineering. Int. J. Prod. Res. **56**(1-2), 224–237 (2018)
2. De Mauro, A., Greco, M., Grimaldi, M.: What is big data? a consensual definition and a review of key research topics. In: AIP Conference Proceedings, vol. 1644, no. 1. AIP (2015)
3. Tolio, T., et al.: SPECIES - co-evolution of products, processes and production systems. CIRP Ann. **59**(2), 672–693 (2010)
4. Colledani, M., et al.: Design and management of manufacturing systems for production quality. CIRP Ann. **63**(2) 773–796 (2014)
5. Tao, F., et al.: Data-driven smart manufacturing. J. Manufact. Syst. **48**, 157–169 (2018)
6. Monostori, L., et al.: Cyber-physical systems in manufacturing. CIRP Ann. **65**(2) 621–641 (2016)
7. Colledani, M., Tolio, T., Yemane, A.: Production quality improvement during manufacturing systems ramp-up. CIRP J. Manuf. Sci. Technol. **23**, 197–206 (2018)
8. Djurdjanovic, D., Ni, J.: Stream-of-variation (SoV)-based measurement scheme analysis in multistation machining systems. IEEE Trans. Autom. Sci. Eng. **3**(4), 407–422 (2006)
9. Djurdjanović, D., Jiao, Y., Majstorović, V.: Multistage manufacturing process control robust to inaccurate knowledge about process noise. CIRP Ann. **66**(1), 437–440 (2017)
10. Umeda, Y., et al.: Product modularity for life cycle design. CIRP Ann. **57**(1) 13–16 (2008)
11. Ijomah, W.L., et al.: Development of design for remanufacturing guidelines to support sustainable manufacturing. Robot. Comput.-Integr. Manuf. **23**(6) 712–719 (2007)
12. Eger, F., et al.: Zero defect manufacturing strategies for reduction of scrap and inspection effort in multi-stage production systems. Procedia CIRP **67**, 368–373 (2018)
13. Laipple, G., et al.: Aggregated hierarchical modeling and simulation in semiconductor supply chains. In: 2018 Winter Simulation Conference (WSC). IEEE (2018)
14. Tolio, T., Copani, G., Terkaj, W.: Key research priorities for factories of the future—part II: pilot plants and funding mechanisms. In: Factories of the Future, pp. 475–494. Springer, Cham (2019)
15. Terkaj, W., Tullio T., Valente, A.: Designing manufacturing flexibility in dynamic production contexts. In: Design of Flexible Production Systems, pp. 1–18. Springer, Heidelberg (2009)
16. Ilyas, M., Mahgoub, I.: Smart Dust: Sensor Network Applications. Architecture and Design. CRC Press, Boca Raton (2018)
17. Esmaeilian, B., Behdad, S., Wang, B.: The evolution and future of manufacturing: a review. J. Manuf. Syst. **39**, 79–100 (2016)

18. Colledani, M., Magnanini, M.C., Tolio, T.: Impact of opportunistic maintenance on manufacturing system performance. CIRP Ann. **67**(1) 499–502 (2018)
19. Jeschke, S., et al.: Industrial internet of things and cyber manufacturing systems. In: Industrial Internet of Things, pp. 3–19. Springer, Cham (2017)
20. Koren, Y., Wang, W., Xi, G.: Value creation through design for scalability of reconfigurable manufacturing systems. Int. J. Prod. Res. **55**(5), 1227–1242 (2017)
21. Gu, X., et al.: Manufacturing system design for resilience. Procedia CIRP **36**, 135–140 (2015)
22. Koren, Y., Xi, G., Guo, W.: Reconfigurable manufacturing systems: principles, design, and future trends. Front. Mech. Eng. **13**(2), 121–136 (2018)
23. Rossi, F., et al.: A systematic methodology for the modularization of manufacturing systems during early design. Flex. Serv. Manuf. J. 1–44 (2019)
24. Battaïa, O., et al.: Design for manufacturing and assembly/disassembly: joint design of products and production systems. Int. J. Prod. Res. **56**(24), 7181–7189 (2018)
25. Tan, C., et al.: Product personalization enabled by assembly architecture and cyber physical systems. CIRP Ann. **66**(1), 33–36 (2017)
26. Wang, L., Törngren, M., Onori, M.: Current status and advancement of cyber-physical systems in manufacturing. J. Manuf. Syst. **37**, 517–527 (2015)
27. Babiceanu, R.F., Seker, R.: Big data and virtualization for manufacturing cyber-physical systems: a survey of the current status and future outlook. Comput. Ind. **81**, 128–137 (2016)
28. Tomiyama, T., Moyen, F.: Resilient architecture for cyber-physical production systems. CIRP Ann. **67**(1), 161–164 (2018)
29. Kozjek, D., et al.: Distributed control with rationally bounded agents in cyber-physical production systems. CIRP Ann. **67**(1), 507–510 (2018)
30. Tsukune, H., et al.: Modular manufacturing. J. Intel. Manuf. **4**(2), 163–181 (1993)
31. Wu, K., Zhou, Y., Zhao, N.: Variability and the fundamental properties of production lines. Comput. Ind. Eng. **99**, 364–371 (2016)
32. Ni, J., Xi, G., Jin, X.: Preventive maintenance opportunities for large production systems. CIRP Ann. **64**(1), 447–450 (2015)
33. Glock, C.H., Grosse, E.H.: Decision support models for production ramp-up: a systematic literature review. Int. J. Prod. Res. **53**(21), 6637–6651 (2015)
34. Xu, Y., Helal, A.: Scalable cloud–sensor architecture for the Internet of Things. IEEE Internet Things J. **3**(3), 285–298 (2016)