Decision making for fast productivity ramp-up of manufacturing systems

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Abstract. Frequent changes in demand and production context call for frequent modifications in manufacturing systems, which can be realized by reconfigurations. After a modification, a manufacturing system usually fails short in delivering the expected production performance, due to an increased production of defective items and unexpected machine failures caused by incomplete or inadequate changes/reconfigurations implemented at physical or control levels. The time between the production of the first part and the stable production of good parts at the target effective throughput level is called the ramp-up time. Labor-intensive, time-consuming and expensive interventions are needed to understand and address issues that affect ramp-up. This essay provides a comprehensive overview on the topic, by addressing the following aspects: (i) definition of productivity ramp-up and brief explanation of the problem, (ii) research presented in the literature as solution approaches, (iii) selection of methodologies and their implementation, (iv) examples of applications, (v) research directions.

Keywords: Ramp-up, Manufacturing Systems, Reconfigurability.

1 Introduction

In manufacturing companies, the ability to timely deliver the desired quantities of products that are conforming to customer expectations strongly depends on how the company is capable to deal with changes in the Product-Process-Production system.

The increasing product variety and customization have significantly reduced production lots, thus making traditional mass production contexts infrequent. Moreover, the fast introduction of emerging manufacturing and sensor technologies has significantly reduced innovation cycles, causing the need for continuous adaptations of the system configuration to integrate advanced technological enablers. Furthermore, reconfigurability, changeability and co-evolution are nowadays accepted paradigms in industry, enabling a strong coordination between the dynamics of the system lifecycle and the dynamics of the product and process lifecycles. As a consequence, manufacturing systems continuously evolve during their lifecycle (Monostori 2020).

Changeability encompasses an organization's readiness and capability to embrace change, both internally and externally. It involves an organization's willingness to adjust its strategies, processes, and structures to meet evolving demands and challenges. Productivity ramp-up, on the other hand, refers to the transitional period during which an organization aims to increase its operational efficiency and output after implementing changes, such as introducing new technologies, launching a new product line, or reorganizing its workforce (Nassehi 2022). The link between changeability and productivity ramp-up is deeply rooted in their symbiotic nature (Andersen 2016). Organizations that prioritize and cultivate a culture of changeability are more likely to experience smoother and more rapid productivity ramp-ups (Schmitt 2020). The ability to respond swiftly to emerging opportunities or challenges enables such organizations to capitalize on favorable conditions or mitigate risks effectively. Furthermore, a proactive approach to change fosters a workforce that is more receptive to new processes and technologies, reducing resistance during the productivity ramp-up phase (Minguillon 2019).

Agility and adaptive capacity are key components of changeability that directly impact productivity ramp-up. Agile organizations possess a dynamic and nimble infrastructure that can swiftly reallocate resources and recalibrate strategies as circumstances evolve. This trait is invaluable during productivity ramp-up, as it allows organizations to seize opportunities with minimal delays and optimally allocate resources during the transitional phase (Bergs 2021). Additionally, an adaptive culture encourages employees to embrace change positively, facilitating the integration of new practices and technologies into their workflow.

Modern manufacturing systems are complex cyber-physical systems that are increasingly required to adapt to fluctuations in demand. Such adaptation requires reconfiguration and other changes in the machines and processes that comprise the system (Magnanini 2022). The amount of time between consecutive major changes in manufacturing systems has been reducing due to the frequent need for reconfiguration, adoption of new technologies, and the introduction of new digital innovation solutions for optimal operations (Cerqueus 2023).

After a modification, a manufacturing system usually fails short in delivering the expected production performance, due to an increased production of defective items and unexpected machine failures caused by incomplete or inadequate changes/reconfigurations implemented at physical or control levels. Labor-intensive, time-consuming and expensive interventions are needed to understand and address issues that affect ramp-up time, namely the time between the production of the first part and the stable production of good parts at the target effective throughput level (Colledani 2018).

The increased frequency of ramp-up events has resulted in new research and practical applications. These activities have identified opportunities to design comprehensive methods for effective evaluation and management of ramp-up. Indeed, the growing deployment of cyber-physical solutions such as digital information and communication technologies opens new opportunities for productivity management in manufacturing companies, with an estimated average increase in productivity of 32% by 2025 due to digitalization (Jeske 2018). This increase in productivity can be linked to the way digitalization changes the handling of data and information by offering new and extended ways for collecting, transferring, evaluating, and exploiting information, all of which are opportunities that allow increases in effectiveness and efficiency.

This essay aims at structuring the knowledge about the topic of productivity ramp-up, challenges and main issues towards its management and optimization, as well as state-of-the-art methodologies for decision-making. Firstly, Section 2 introduces the definition of productivity ramp-up and brief explanation. Secondly, Section 3 reviews available methodologies and solution approaches, according to multiple research lines. In Section 4, a selection of these methodologies are explained in details to serve as starting research problems for researchers and practitioners. Section 5 elaborates on this by presenting industrial applications from literature. Then, future research direction are outlined in Section 6, and conclusion and remarks are provided in Section 7.

2 Challenges related to ramp-up

The goal of this Section is to provide a systematic description of emerging challenges related to productivity ramp-up in modern manufacturing systems. First, the concept of productivity ramp-up in a manufacturing system is defined. Then, the root-causes available in the literature for ramp-up generation are presented. Finally, an overview of the decision-making problems related to productivity ramp-up is provided, along with a discussion of the lifecycle of manufacturing systems.

2.1 Definition of productivity ramp-up

The ramp-up phase can be defined as the process of bringing a production system up to its expected operational characteristics after it has been designed and built and before it is taken into full operation (Doltsinis 2020). The ramp-up time, also known as the time to volume, is the time span between the production of the first part and the stable production of good parts at the target effective throughput level, following the green-field implementation or a major reconfiguration (brown-field) in the considered manufacturing system (Colledani, 2018).

Ideally, a zero ramp-up time would be desirable, as the target effective production rate would be reached without any production loss. However, in real systems this ideal condition is not achieved due to several causes for production losses. Hence, the productivity ramp-up can be examined by plotting the throughput as a function of time as shown in Fig. 1.

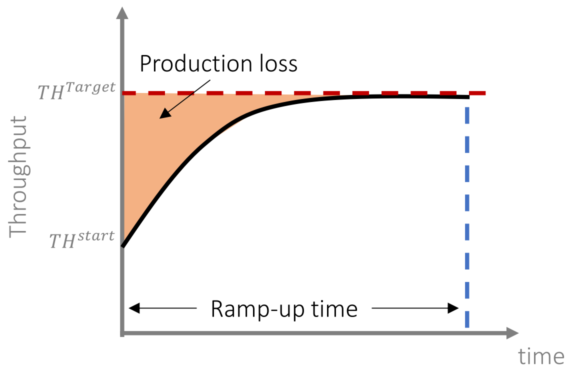

Figure 1. Schematical representation of productivity ramp-up in manufacturing systems.

The horizontal red line represents the target effective production rate, or throughput, TH^{Target}, of the system after a configuration (*green field*) or reconfiguration (*brown field*) that ends at time $t = 0$. The black curve represents the average effective throughput (production rate) TH^{Eff} curve observed in the actual system after a reconfiguration. For example, TH can be the average daily, or single shift, throughput. The ramp up time indicated as a black arrow on the horizontal axis, is the time the system requires to reach the target effective throughput. The shaded area indicates the cumulative production loss, P^{Loss}, observed during ramp-up, which can be expressed as follows:

$$P^{Loss} = \int_{t=0}^{t=t_{ramp}} (TH^{Target} - TH^{Eff}(t)dt$$

Generally, the productivity ramp-up can be complicated to assess, and companies may rely on synthetic indicators such as the overall equipment effectiveness and its trend.

2.2 Root-causes for ramp-up in manufacturing systems

Manufacturing systems are complex objects which include a variety of resources, both hardware and software. When it comes to ramp-up of manufacturing systems, root-causes can be identified linked to the different aspects dealing with the integration of resources and workforce. Indeed, following the advent of Industry4.0, resources of manufacturing systems are more and more intertwined, not only from the physical point of view but also from the digital point of view (Stark 2019).

As a consequence, the reasons for productivity ramp-up in modern manufacturing systems can be traced to manifold aspects, including technological, organizational and software aspects (Colledani 2018).

Indeed, when the reduction of ramp-up is targeted as production objective, technological innovations are pushed towards new solutions, which allow for fast implementation, and also fast reconfiguration (Diaz 2022). From the point of view of implementation, several reasons for ramp-up can be traced to technological aspects, including low process quality, long set up needed for the adjustments to new production, tuning of process parameters and fixing the final production cycle when multiple operations are involved (Huang 2019).

Problems encountered during this phase include disturbances in process and product quality, a lack of reliable planning, unplanned capacity losses, and poor performance of suppliers (Islam 2022).

From the organizational viewpoint, the ramp-up phase can be considered a learning process that could be reflected in better usage of the equipment, in the continuous improvement of product quality, and in the reduction of labor requirements (Glock 2020). Indeed, the ramp-up phase represents the moment where human decision-makers are mostly involved during the system life cycle.

Finally, digitalization both helps and complicates ramp-up. Rapid evolution of digital solutions has led to a high variety of software for communication and integration protocols (Ugarte 2022). Often, the deployment of these solutions at shop-floor level is not trivial especially when new connections are involved. As a consequence, software aspects cannot be avoided in the ramp-up management.

2.3 Decision-making for optimizing ramp-up

According to the decision instant, different strategies, as well as a combination of all, can be used to reduce the ramp-up in manufacturing systems. Production ramp-up is a decision-making process where human experts decide on the best actions to fine-tune the process. It is a highly complex parameter tuning process with many inter-related factors leading to a well-defined goal. In the following, an overview is provided, according to the timeframe in which the problem is addressed along the manufacturing system lifecycle.

Design phase

In the design phase, especially in the green-field design, it is necessary to anticipate problems related to the ramp-up of the manufacturing system. In this phase, most of the burden is on the system provider or the machine tool builder. These actors should guarantee that the upcoming ramp-up of the manufacturing system goes as smooth as possible.

Some reasons include poor understanding of the physical phenomena happening in the real system; wrong system requirement definition in the design phase; poor system design (hardware and control); unknown internal disturbances as machine failures and quality problems.

Decision-making problems in this case contribute to the reduction of the throughput losses by enabling to start the production with a system providing an effective throughput which is closer to the target, as depicted in Fig. 2.

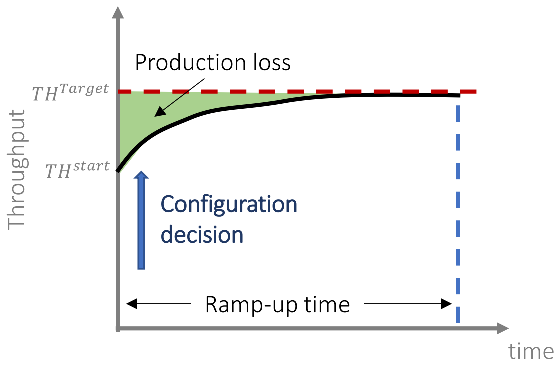

Figure 2. Effects of design decisions on ramp-up.

As it can be noticed, taking better decisions during the design phase of a manufacturing system allows to overall reduce the production loss, even without affecting the ramp-up duration. Indeed, the anticipation of potential ramp-up problems provides a system design that is more robust to disturbances, thus enabling a performance improvement by design. Strategies in this phase may include the implementation of virtual commissioning in order to guarantee a smooth integration of technologies, as well as optimal configurations by means of model-based methods.

Operational ramp-up

Once the manufacturing system has been installed at the manufacturing company's premises, ramp-up does exist because unexpected problems occur that had not been included in the design phase. Some examples include interface problems related to raw materials may have a different physical behavior; suppliers may need to adapt to the new system; organizational rules may delay the implementation; and also human-related issues. In fact, since the human being is autonomous by definition, impossible to model and source of innovation and disruption at the same time for the system. At the same time, solutions may come from the operators that force to re-think the system.

Decision-making problems in this case contribute to the reduction of the throughput losses in a two-fold way: (i) by shortening the ramp-up time or (ii) by improving the ramp-up management. These two effects of decision-making during ramp-up are depicted in Fig. 3.

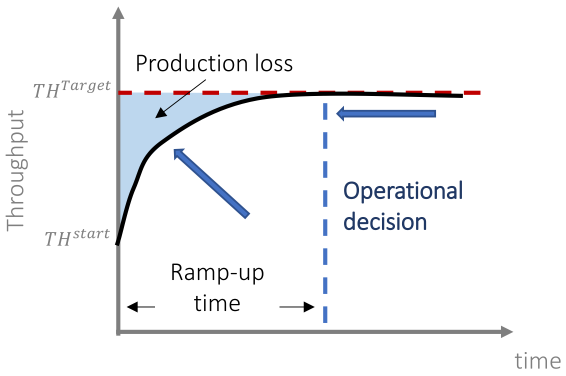

Figure 3. Effects of operational decisions on ramp-up.

On one hand, an optimal ramp-up management avoids having much production losses because a higher productivity is reached. In order to do so, production bottlenecks should be identified and solved, as well as organizational issues as workforce training, or supplier management. On the other hand, these improvement actions should be performed without any time delay to avoid long ramp-up durations.

Multiple ramp-up

The effective throughput loss problem is even more significant in the presence of multiple reconfigurations of the system. In this case, the production loss may account not only for those during the ramp-up, but also during the reconfiguration, as it is depicted in Fig. 4.

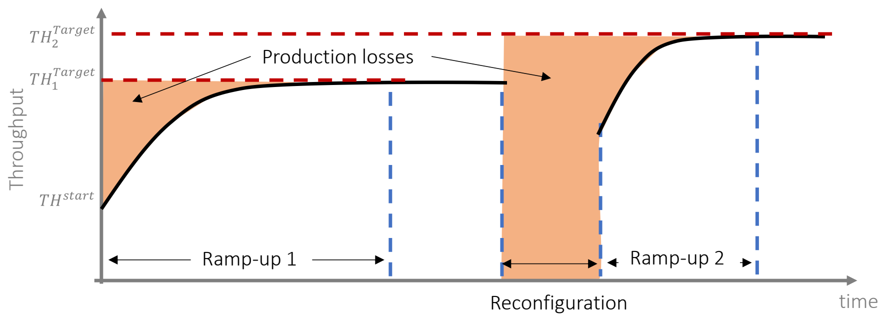

Figure 4. Effects of multiple reconfigurations on ramp-up.

After the first configuration reaches the target effective throughput level, a system reconfiguration takes place. During the reconfiguration time, the system is not delivering parts and the effective production rate is zero. Once the system is restarted, a new ramp-up is observed, that brings the system to the new target effective throughput level in the new configuration. Additional production losses are then observed, that directly affect the profitability of the new configuration. It is worth to notice that the not unusual case in which the initial effective throughput of the new configuration is lower than the target effective throughput of the previous configuration is represented in Fig. 2. Given the relevance of the effective throughput losses during the system ramp-up along the system life-cycle, it is important to deeply understand the causes for these losses.

3 Review of available novel solution approaches

State-of-the-art works related to productivity ramp-up are articulated following a high variety of topics. This Section provides an overview of the related works with respect to the decision-making problems for reducing productivity ramp-up in manufacturing systems, as they were presented in Section 2.

The articles have been selected with a structured research in Scopus, WoS and Google Scholar databases, following these steps:

1. Implementation of database queries addressing selected keywords and limiting the time frame to the last 5 years:
   a. (ramp-up AND (manufacturing OR production) AND systems);
   b. ((changeable OR reconfigurable) AND (manufacturing OR production) and systems);
   c. (reconfiguration AND (manufacturing OR production) AND systems)
2. Filtering of first papers selection based on abstracts, keywords and publication journals.
3. Extension of articles selection by means of referenced works. Only milestone works have been considered outside of the 5-year time frame.

An overview of the state of the art is presented in Table 1. In this Table, the selected works have been grouped according to the similarity in the solution approach, and classified according to the ramp-up target phase and objective as in Section 2. It can be noticed that the variety of solution approaches spans over manifold aspects of decision-making for productivity ramp-up, from software management, as in virtual commissioning, to hardware decisions, as technological reconfiguration, to resource and workforce management, to re-thinking completely manufacturing systems in order to minimize multiple ramp-ups as in matrix production systems and line-less manufacturing.

Table 1. Overview of approaches for ramp-up decision making.

Solution approach	Reference	Target phase	Objective
Integrated technological and operational strategies	Andreev, 2021 Doltsinis, 2020 Frazzon, 2018 Jeske, 2019 Lai, 2021 Magnanini, 2021	Operational ramp-up	Productivity maximization during ramp-up
Risk-oriented ramp-up management	Elstner and Krause, 2014 Medini, 2020	Operational ramp-up	Productivity maximization during ramp-up

	Mamaghani, 2021 Medini, 2021		
Configuration optimization	Islam, 2022	Design phase	Improvement of productivity
Matrix production systems design and operations	Stricker, 2021 Trierweiler, 2021	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
Line-less manufacturing management	Buckhorst, 2022 Göppert, 2020 Göppert, 2021 Grahn, 2022 Schmitt, 2021	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
Plug-and-produce systems	Wurster, 2021 Zimmer, 2019	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
Reconfiguration optimization	Ahmad, 2020 Andersen, 2016 Cerqueus, 2023 Epureanu, 2021 Huang, 2019 Li, 2019 Schmid, 2022	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
Product-oriented ramp-up	Sinnwell, 2019	Design phase	Reduction of ramp-up time
	Bergs, 2021	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
	Ngo, 2020 Schuh, 2015	Operational ramp-up	Productivity and quality maximization during ramp-up
	Slamanig and Winkler, 2011	Operational ramp-up	Reduction of ramp-up time and complexity mitigation
Virtual commissioning	Dammacco, 2022 Krystek, 2019 Ugarte, 2022	Design	Reduction of ramp-up time
	Kampker, 2020 Kampker, 2021	Multiple ramp-up	Reduction of reconfiguration and ramp-up time
Workforce management	Neumann and Medbo, 2017 Lanza and Sauer, 2021 Di Luozzo, 2021 Kim, 2021	Operational ramp-up	Productivity maximization during ramp-up

A significant piece of literature addresses planning and control of production during ramp-up with a focus on productivity and rapidity (Andreev et al., 2021; Magnanini et al., 2021). In this body of literature, the productivity maximization during ramp-up is addressed by integrating decisions related to technological improvements to resources as process machines, and at the same time optimizing the production control and management. Data-driven decision support and mathematical modelling are among the most common solution approaches used in this area (Frazzon et al., 2018; Jeske et al., 2019; Doltsinis et al., 2020; Lai et al., 2021).

Complementarily some research works addresses productivity ramp-up projects from a cost-benefit perspective with the aim to proactively respond to market needs and mitigate failure risk (Elstner and Krause, 2014; Medini et al. 2020; Medini et al., 2021; Mamaghani and Medini, 2021). An empirical research outlined different categories of factors to be considered during development projects, which could affect ramp-up and operational performance (Islam et al., 2022). In a recent study, Medini (2022) highlighted standardization and integration as complementary principles to scale up and ramp-up in production.

In response to increased variety and shortened product life cycle concepts such as matrix manufacturing systems have emerged. According to this concept, resources and processes and organized into modules, process modules are linked using process flows. This architecture allow to flexibly produce variants of the product for which resources are available within the system (Trierweiler and Bauernhansl, 2022). Heuristics and simulation are among the used approaches to address scheduling and reconfiguration problems in matrix manufacturing systems (Stricker et al., 2021).

Line-less manufacturing and assembly systems share several properties as matrix manufacturing systems while strongly relying on recent technological developments (Schmitt et la., 2021; Buckhorst et al., 2022). This concept is ruled by three main principles namely, clean floor (e.g. removing obstacle to ease resource movements), mobile production factors (e.g. moving resources), stations on demand (e.g. establish and dissolve stations as per production needs). This concept is enabled through a joint deployment of robotic systems, automated guided vehicles and decision support models (e.g., agent based (Buckhorst et al., 2022), machine learning (Göppert et al., 2020; Grahn et al., 2022)).

The concept of modularity is also as the heart of the fluid automation approach in conjunction with a service-oriented architecture allowing for agile production system (Wurster et al., 2021). This concept is particularly relevant to productivity ramp-up as it allows to reduce reconfigurability efforts through the notion of plug and. Knowledge management over ramp-up projects and decision support systems are crucial for the successful implementation of this concept (Zimmer al., 2019).

The idea of modular processes and resources gave also rise to another research stream focusing on the study of reconfigurability of production systems (Huang et al., 2019; Li et al., 2019) and networks (Epureanu et al., 2021). Reconfigurable manufacturing systems inherit some characteristics from traditional manufacturing concepts augmented with the possibility of capacity scaling-up and performing different functionalities (Andersen et al., 2016). Empirical and case studies fostered the development of this research area (Ahmad et al., 2020; Andersen et al., 2016). Most commonly addressed problems involve design (for scalability) of reconfigurable manufacturing systems, with several solution approaches including linear programming and combinatorial optimization (Li et al., 2019; Cerqueus et al., 2023).

Productivity ramp-up was also addressed from product perspective focusing on aspects such as complexity, innovation and quality (Slamanig et al., 2011; Schuh et al., 2015; Ngo et al., 2020), and using agile and iterative development approaches (Sinnwell et al., 2019; Huang et al., 2019; Bergs et al., 2021).

Industry 4.0 related technologies facilitating digitalization opened up new perspectives to support ramp-up particularly in complex manufacturing systems. This fostered the development of concepts such as virtual commissioning, which aims in short, to validate a (production) system before real implementation (Krystek et al., 2019). To this end, approaches such as virtual reality (Dammacco et al., 2022) and digital twins (Ugarte et al., 2022) are used to virtually validate productivity ramp-up and more largely production system operation. Despite some real case applications mainly as pilot projects, this promising orientation requires further investigation due to its potential in significantly reducing effort, mitigating risks and ensure agility.

Because of ramp-up complexity and high uncertainty, the state of the art also addresses learning effects (Kim et al., 2021) and human performance impact (Di Luozzo et al., 2021) during production ramp-up. The main addressed problems involves planning and performance improvement using simulation (Lanza and Sauer, 2012; Neumann and Medbo, 2017), mathematical modelling (Kim et al., 2021) and performance indicators (Di Luozzo et al., 2021).

4 Description of how to implement novel approaches

In this Section, a selection of novel approaches for decision-making in productivity ramp up is proposed, with respect to the workflow that shall be used in each methodology, the possible implementation software and required inputs. The following novel approaches have been selected in order to approach early researchers to the field and provide clear instructions to the implementation.

4.1 Optimal sequencing of improvement actions

When a manufacturing system faces productivity ramp-up, decisions as minor technological improvement of machines, implementation of control policies, improvement of resource management as reduction of repair time are usually addressed by the company. Each of these improvement actions may have a positive effect on system performance. However, not all improvement actions can be implemented at the same time, for time and resource constraints. Hence, the production manager should decide the sequence of improvement actions in order to maximize the total productivity during the ramp-up, considering the time effort that takes when implementing improvement actions. The complete work can be found in Magnanini (2022).

This method is valid under the following assumptions:

a) Improvement actions are independent among each other;
b) Each improvement action of the set must be implemented;
c) Only one improvement action at a time can be implemented.
d) Each improvement action is characterized by a duration before being fully activated on the system.

The approach is based on the integration of a performance evaluation model and an optimization algorithm. The performance evaluation model is used to model the manufacturing system, as in Discrete Event Simulation (Nassehi 2022) or in analytical models (Magnanini 2023). Each resource in the manufacturing system may be described with characteristics parameters, such as cycle time, time to repair and time to failure. Hence, each improvement action should be described as improvement with respect to one (or more) of these parameters. The performance evaluation model is used to provide key performance indicators, as system throughput, for a given combination of resource parameters, i.e. a configuration.

The problem is approached by means of dynamic programming. Some specific features of the problem make this solution approach viable. Indeed, it can be noticed that the performance in terms of throughput in a given configuration, i.e. for a given subset of already implemented improvement actions, does not depend on the specific sequence used to implement the actions. This can be noticed in Figure 5, where the last two steps of two alternative sequence with same set actions is shown. In particular, all actions from 2 to 7 have been implemented, and only actions 1 and 8 are missing. It is shown that the throughput of the first sequence (blue line) when only 1 and 8 are missing is the same as the one of the second sequence (red line) where the same actions have not been implemented yet (indicated as $th(1{,}8)$ in Figure). Even if both sequence at the end bring the same value of throughput, it can be seen that one permutation dominates the other one. That is, the area above the piecewise linear throughput function is smaller when action 8 is performed first, and then action 1 is performed as last (sequence 1: red line), with respect to that one of sequence 2 (blue line), where action 1 is performed first and action 8 as last one.

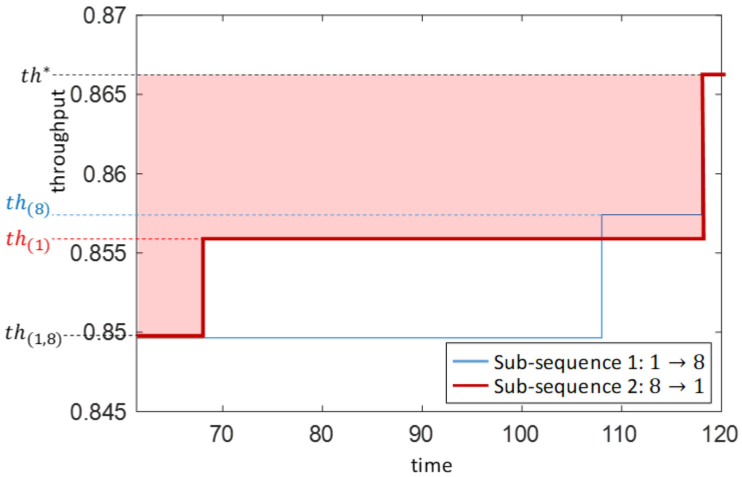

Figure 5. Representation of the approach.

Hence, the problem can be transformed in a minimization problem, where the goal is to minimize the area above the piece-wise linear throughput function. This area can be obtained by simply multiplying the duration and the throughput increment of the selected improvement action, with respect to the previous one.

Formulation 1 (maximization). For a finite set of improvement actions $A = \{a_1, \dots, a_j\}$ acting on the set of configuration parameters $X(s)$ and requiring an implementation time equal to $d(a_j)$, find the sequence $U(S) = \{u_1, u_s, \dots, u_S, u_s \in A\}$ which maximizes the cumulated throughput $TH_{U(S)}$.

Formulation 2 (minimization). For a finite set of actions $A = \{a_1, \dots, a_j\}$ acting on the set of configuration parameters $X(s)$ and requiring an implementation time equal to $d(a_j)$, find the sequence $U(S) = \{u_1, u_s, \dots, u_S, u_s \in A\}$ which minimizes the cumulated lost throughput $\overline{TH}_{U(S)}$.

Therefore, the following dynamic programming approach is used to solve *Formulation 2 (minimization)*.

Step 1. At each decision time s, for all possible combinations $z_k(s) \in Z(s)$, the throughput $th_{z_k(s)}$ is computed by means of the performance evaluation model.

Step 2. For each combination $z_k(s) \in Z(s)$ and for each combination $z_i(s+1) \in Z(s+1)$, so that $z_i(s+1) \subset z_k(s)$, there exists only one arc $\tau_{k,i}$, corresponding to the action $a(\tau_{k,i})$ with duration $d(a(\tau_{k,i}))$. The cost of the arc $\tau_{k,i}$ is computed as

$$c(\tau_{k,i}) = th_{z_k(s)} \cdot d\left(a(\tau_{k,i})\right)$$

Step 3. Starting from decision time S and going backward to the first decision time $s = 1$, the cost-to-go function for each combination $z_k(s)$ at each decision time *s* is computed as

$$C(z_k(s)) = \min_{\mathrm{I}, z_\mathrm{i}(s+1) \subset z_k(s)} \left(c(\tau_{k,i}) + C(z_i(s+1))\right)$$

The sequence of the minimum cost-to-go functions on s minimizes the cumulated lost throughput $\overline{TH}(S)$, and according to *Formulation 2* of the problem it returns the optimal sequence of improvement actions $U(S)$.

Data-driven productivity improvement

In this paragraph, a traditional productivity improvement method is explained, which can be later compared to the sequencing of improvement actions presented in the previous paragraph.

The data-driven productivity improvement is based on dynamic bottleneck identification, enabled by data gathering solutions through IoT. In particular, the examined methodology is based on the Turning Point Method (Lai 2021). This method can be applied to general manufacturing systems with any layout. This approach follows the traditional bottleneck identification method, in which the bottleneck machine is iteratively identified and improvement actions are implemented. All these methods can be defined as 'Bottleneck Release methods', since they iteratively identify the bottleneck, solve it and move to the following bottleneck machine. More details can be found in Li (2009).

The Turning Point Method utilizes the manufacturing system blockage and starvation data to define a bottleneck. The blockage and starvation pattern captures the manufacturing system dynamics by reflecting the nature of workpiece flowing across the production line. Bottleneck stations are ones that tend to cause the upstream stations to be blocked and downstream stations to be starved. Besides, bottleneck stations usually have higher utilizations compared to nearby stations, therefore with a lower total blockage plus starvation time than its adjacent stations.

Therefore, the "turning point" can be defined at the stations where the trend of blockage and starvation turns from higher blockage over starvation to higher starvation over blockage. Besides, the "turning point" stations must also satisfy having less total blockage plus starvation time over its two neighboring stations. The mathematical definition is shown below:

Definition: Station is the turning point in an station segment with finite buffers during a period if:

$$(TB_i - TS_i) > 0 : i \in [1, \dots, j-1], j \neq 1, j \neq n$$
$$(TB_i - TS_i) < 0 : i \in [j+1, \dots, n], j \neq 1, j \neq n$$
$$TB_j + TS_j < TB_{j-1} + TS_{j-1}, j \neq 1, j \neq n$$
$$TB_j + TS_j < TB_{j+1} + TS_{j+1}, j \neq 1, j \neq n$$
$$if\ j = 1 : (TB_1 - TS_1) > 0\ and\ (TB_2 - TS_2) < 0\ and\ TB_1 + TS_1 < TB_2 + TS_2$$
$$if\ j = n : (TB_{n-1} - TS_{n-1}) > 0\ and\ (TB_n - TS_n) < 0\ and\ TB_n + TS_n < TB_{n-1} + TS_{n-1}$$

Where
TB_j : blockage time of station j
TS_j : starvation time of station j

The blockage time and starvation time can be computed by means of data-driven approaches, as in real manufacturing systems where IoT data are gathered (Lai 2021), or also using performance evaluation models such as Discrete Event Simulation.

4.2 Multi-agent systems for assessing production ramp-up strategies

Multi-agent systems have been applied to various problems in manufacturing in conjunction with other production management concepts. Agents' autonomy and interaction are among the key features, which increased their potential for high uncertainty situations such as ramp-up (Rodrigues et al., 2018; Medini et al., 2021). This section reports on a multi-agent system to support ramp-up planning. The system was designed and implemented following the GAIA methodology (Wooldridge, 2000). The proposed approach aims to enlighten decisions regarding ramp-up planning strategies identified from the literature (Schuh et al., 2005; Slamanig and Winkler, 2011). Variety and volume are among the key criteria defining a strategy. For instance, selecting a high-volume low-mix or low-volume high-mix strategy depends on a variety of factors including complexity, cost and selling prices. The multi-agent system will help model the real production system and simulate its behavior considering different planning strategies.

The designed system consists of a set of autonomous agents interacting together and representing processes involved in production within a single echelon make-to-order supply chain. An agent can be seen as *a computer system located in an environment that operates autonomously and flexibly to achieve the objectives for which it was designed* (Jennings et al., 1998). The methodology is ruled by the following hypotheses: the focus is put on a focal company within the supply chain, internal organization of the customer and suppliers is not addressed; the methodology is intended for single and multivariant production contexts. A simplified overview of agents' roles is shown hereafter. These roles are inspired by the SCOR (Supply Chain Operations Reference) model which provides a standard representation of processes across supply chains (Medini and Rabénasolo, 2014).

- *Customer*: generates and sends orders to *Company*.
- *Company*: receives and processes *Customer* orders, manages inventories, and generates production and supply orders.
- *Production*: receives, processes and delivers production orders from *Company* and updates production load.
- *Performance*: tracks and updates performance indicators.
- *Supplier*: receives, processes and delivers *Company* supply orders.

The sequence of interactions among agents is represented in Figure 6 using a sequence diagram. This example represents a typical scenario for order processing and does not cover issues and unplanned events.

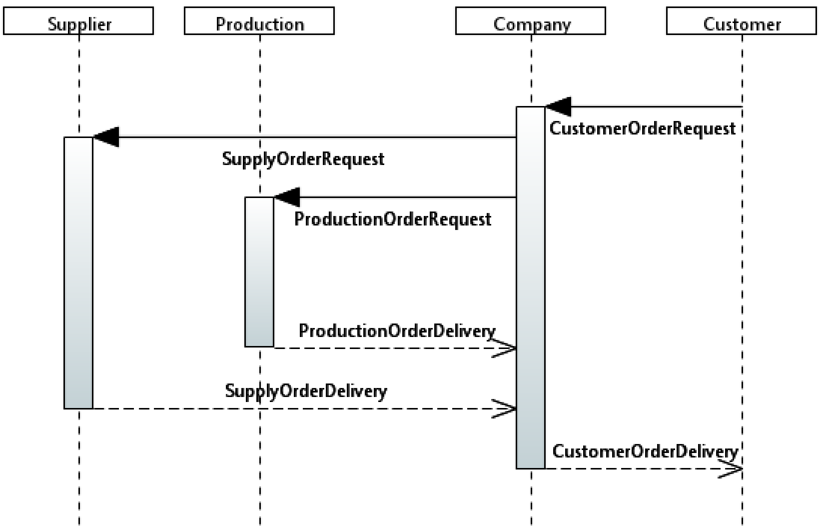

Figure 6. Agents interactions sequence

Agents allow collectively to implement the following model intended for evaluating different planning strategies of production ramp-up. A strategy is represented by a matrix S with p_i^t is the production volume of product i at planning period t, T and M are respectively total planning periods and total number of products within focal company's portfolio. The strategy is defined and implemented by *Company* and *Production* agents. *Customer* and *Supplier* allows to replicate supply chain operation consistently with SCOR model.

$$S = (p_i^t)_{i=1\ldots M, t=1\ldots T}$$

p_i^t is calculated according to the following equation, where s_i^t is the share of product i in product mix at period t, $P^t$is the aggregate production capacity at period t. s_i^t depends on product complexity C_i, planned aggregate capacity P^t and it is valued by decision makers involved in ramp-up management.

$$p_i^t = s_i^t \times P^t$$

Since the model is consistent with a make-to-order configuration, the effective production volumes depends on received customer orders as shown in the following equation with $e_i^t \leq p_i^t$.

$$e_i^t = \sum_i d_i^t$$

Three main performance aspects are covered by the model, cost, lead-time and sales revenue. These are addressed through several indicators updated by *Performance* agent. Indicators are updated at predefined points of time. Total cumulative cost at period t is calculated according to the following equation with $C_T^0 = 0$, c_S^t, c_P^t, and c_I^t are respectively the costs related to supply, production and inventory captured at period t.

$$C_T^t = C_T^{t-1} + (c_S^t + c_P^t + c_I^t) \ \forall t \in \{1..T\}$$

Average cost and lead-time are incrementally updated according the following equations, respectively, LtT is the average lead-time at t with $L_T^0 = 0$.

$$C_A^t = \frac{C_A^{t-1} + (c_S^t + c_P^t + c_I^t)}{2} \ \forall t \in \{1..T\}$$

$$L_A^t = \frac{L_A^{t-1} + L^t}{2} \ \forall t \in \{1..T\}$$

Similarly, cumulative sales turnover, s_T^t, is updated according to the following equation, with $s_T^0 = 0$, s_t^v and q_t^v refer respectively to selling price of variant v and quantity per order.

$$s_T^t = s_T^{t-1} + (s_t^v \times q_t^v) \ \forall t \in \{1..T$$

5 Exemplary detailed implementation of the solution approaches

In this Section, exemplary applications of the solution approaches presented in Section 4 are provided. The aim of this Section is to provide practitioners and young researchers with viable examples to be implemented in the field, before addressing more complex applications as will be shown in later Sections.

5.1 Sequencing of ramp-up actions in automated assembly lines

This section reports an exemplary implementation of the methodology explained in Section 4.1. Further details can be found in Magnanini (2022). The reference system

which is considered is a multi-stage automated assembly line, with inter-operational buffers. A simple system is used as test bed for the application of the methodologies. On the other hand, different experiments are conducted in order to compare the results of the methodologies according to the system characteristics.
The completely balanced line example is composed of 3 stages and 2 buffers. Each machine is presented with deterministic cycle time (CT), time to repair exponentially distributed with main parameter Mean Time to Repair (MTTR) and time to failure exponentially distributed with main parameter Mean Time to Failure (MTTF). The isolated availability can be obtained as $\frac{MTTF}{MTTR+MTTF}$, while the isolated throughput can be obtained as $\frac{1}{CT} \cdot \frac{MTTF}{MTTR+MTTF}$. The parameters of the stages are represented in Table 2. Performance evaluation of the resulting manufacturing system can be obtained by means of Discrete Event Simulation (Nassehi 2022), or Markovian modelling (Magnanini 2023).

Table 2. Improvement Actions for the first case of the completely balanced line

The first set of improvement actions includes the same percentage change for each stage parameter and their duration of implementation is equal. Therefore, the duration of implementation is becoming a non-constraint parameter for this case.

Stage	CT (s)	MTTF (s)	MTTR (s)	Isolated Throughput (parts/s)	Isolated Availability
M_1	3	3000	1500	0.22	0.67
M_2	3	4000	2000	0.22	0.67
M_3	3	5000	2500	0.22	0.67

In Table 3, the improved machine parameters and corresponding machines are represented. The improvements are only one percent increase in the machine and each improvement action takes 1 week to be implemented.

Each improvement action has a positive effect on the system throughput with respect to what it was at decision time before it was implemented as in Figure 4. The set of improvement actions may include the replacement of pneumatic actuators with electric ones, having positive effect on the cycle time, or the implementation and refinement of predictive maintenance algorithms, having a positive effect on time to failure, or organizational improvement, having positive effect on time to repair. Further examples of improvement actions targeting similar manufacturing systems can be found in Magnanini (2021), Islam (2022), Frazzon (2018).

Table 3. Improvement actions for the first case of the completely balanced line

Improvement action	Improved machine	Target parameter	Effect on the parameter	Duration
1	M_1	CT	-1%	1 week

2	M_2	CT	-1%	1 week
3	M_3	CT	-1%	1 week
4	M_1	MTTR	-1%	1 week
5	M_2	MTTR	-1%	1 week
6	M_3	MTTR	-1%	1 week
7	M_1	MTTF	-1%	1 week
8	M_2	MTTF	-1%	1 week
9	M_3	MTTF	-1%	1 week

When the duration of implementation is not a concern, bottleneck release can give the optimal sequence since it can also identify the best improvement to increase system throughput the most at each step.

Optimal sequence : 1 → 2 → 3 → 5 → 6 → 4 → 8 → 9 → 7

Since the average buffer capacities of the system are not operating at the full capacity, the system wants firstly to push and increase the stages cycle times iteratively starting from the first machine. Furthermore, the middle machine acts as the bottleneck in a completely balanced line. Therefore, improvement of the meantime to repairs are starting from the middle machine and so does the improvement of mean time to failures.

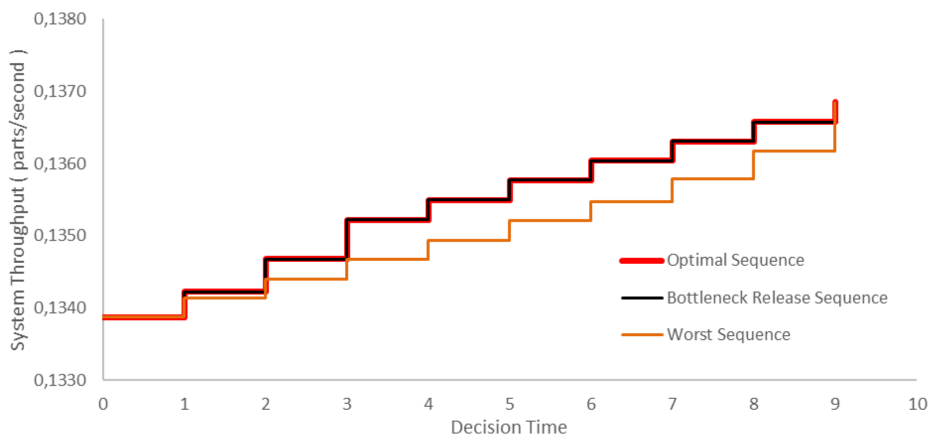

Figure 7. Sequence of improvement actions for first case.

It is interesting to explore also the case in which the improvement actions are defined only on one parameter, i.e. cycle time, as included in Table 4.

Table 4. Improvement Actions for the second case of the completely balanced line

Improvement action	Improved machine	Target parameter	Effect on the parameter	Duration
1	M_1	CT	-1%	1 week
2	M_2	CT	-1%	1 week
3	M_3	CT	-1%	1 week

4	M_1	CT	-3%	3 week
5	M_2	CT	-3%	3 week
6	M_3	CT	-3%	3 week
7	M_1	CT	-7%	7 week
8	M_2	CT	-7%	7 week
9	M_3	CT	-7%	7 week

The bottleneck release sequence seems to be very obvious since there is only one parameter to be improved and the bottleneck release identifies the bottleneck machine and tries to improve the system throughput at most.

However, the optimality of the cumulative production cannot be always achieved with the straightforward approach where most of the companies prefer this approach. The optimal sequence and the bottleneck release sequence are presented below.

Optimal sequence : 7 → 8 → 3 → 9 → 2 → 4 → 5 → 6 → 1

Bottleneck Release Sequence : 7 → 8 → 9 → 4 → 5 → 6 → 1 → 2 → 3

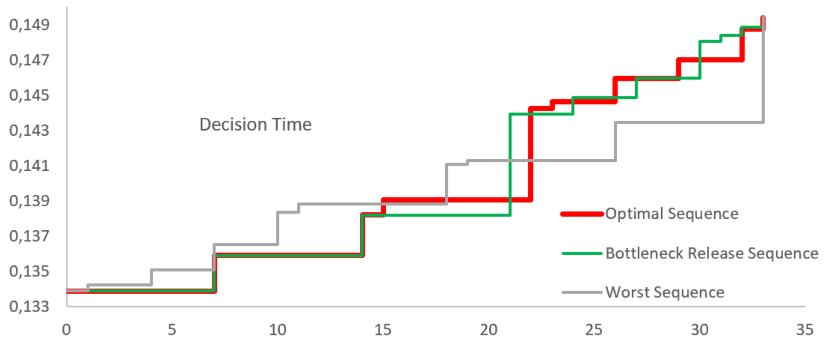

Figure 8. Sequence of improvement actions for second case.

It is worth noticing that both approaches do not account for the action cost, hence a completely different approach should be used in case both cost and implementation time is required to be considered.

5.2 Ramp-up strategies assessment for a kitchen manufacturer

This section reports on a prototypical implementation of the model presented in section 4.2 using a case company in the furniture sector. In this sector, manufacturers are compelled to diversity their offering in order to align with various customer requirements. SMEs (Small and Medium-sized Enterprises) in particular, require decision-making support on the strategic and tactical levels. The case company is an SME located in Europe proposing a large panel of kitchen types. A modular architecture is a characteristic of most of the offered kitchens, with the cabinet being a key module in all kitchen types. Unlike several competitors, the case company offers the option to customize the dimensions of kitchen cabinets, which is generally more difficult to implement.

The model is implemented using JADE platform (Java Agent Development Environment) allowing for modelling and simulating supply chain processes by setting agents' behaviors and populating the model with data from the case company.

- *Customer* behaviors: *OneShotBehaviour* for the initialization (e.g. loading bill of material data, possible product configurations (solution space), order arrival rate), *TickerBehaviour* for order generation, these behaviors are executed in a sequence through a *SequentialBehavior*.
- *Company* behaviors: *OneShotBehaviour* for the initialization (e.g. master production data, product portfolio), *CyclicBehaviour* for processing orders, *TickerBehaviour* for production orders generation and inventory update; these are executed in parallel through a *ParallelBehaviour*.
- *Production* behaviors: *WakerBehaviour* for confirming production orders delivery based on workload and production lead-time.
- *Supplier* behaviors: include *SimpleBehaviour* to receive and process orders.
- *Performance* behaviors: *TickerBehaviour* for updating indicators values (simulation is also terminated by *Performance* agent).

The main data from the case company involves six cabinet variants having different sizes, unit cost, production lead-time and selling prices. Variants are referred to by 0, 1, 2, 3, 4 and 5, with selling prices of €550, €500, €350, €400, €600, €650, respectively. These prices depends on assemble time and cost.

The two scenarios compared are HV-LM (High Volume - Low Mix) consisting of focusing primarily on variants 2 and 3, which are relatively standard and cost-efficient ones, and LV-HM (Low Volume - High Mix) consisting of launching all variants with a share of 10% for each of variants 0 and 6 and 20% for each of the other variants.

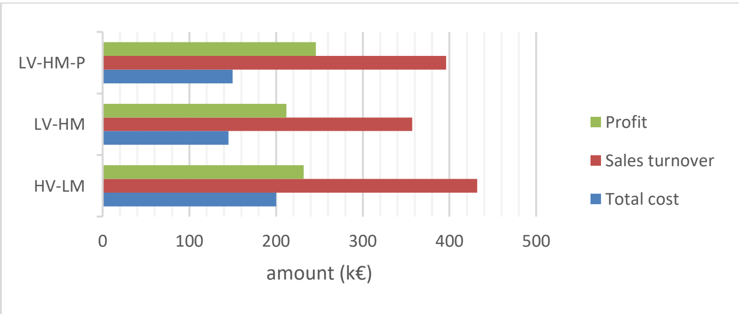

Figure 9. Performance results of two strategies

Comparing the results from the two scenarios HV-LM and LV-HM indicates that the former seems to be more profitable for the company, around 10% higher than LV-HM. Sales turnover is also higher when adopting a HV-LM strategy. These results can be explained by the decrease of productivity and increase of costs due to higher complexity of variants 0.1,4 and 5, when adopting a LV-HM strategy. The third scenario, corresponds to a LV-HM strategy but with a slight increase in selling prices (around 6%). This scenario outperforms the HV-LM with 10% of higher profit although sales turnover is still lower than first scenario. This indicates the relevance of pursuing an

HV-LM strategy while revising selling prices to enhance the economies of scope (Low Volume – High Mix – higher Price (HV-LM-P)). This is evidenced further by the rate of return, which climbs from 0.54 in the HV-LM scenario to 0.61 in LV-HM-P.

6 Industrial applications

In this Section, examples from industrial applications are provided in order to give an overview of the implementation challenges which may arise.

6.1 Decision Support System integrating learning effect

In this Section, an example of decision support system integrating learning effects and aspects for rapid ramp-up is presented. The example is taken from Doltsinis (2020). Ramp-up requires different decision support strategies that incorporate both model-based and model-free learning. These learning methods are activated through two operating modes, the offline and online. This is a result of the process data flow and depends on the systems ramp-up state and the previously acquired experience. The overview of the proposed decision support system integrating the data flow and the building blocks is shown in Figure 10.

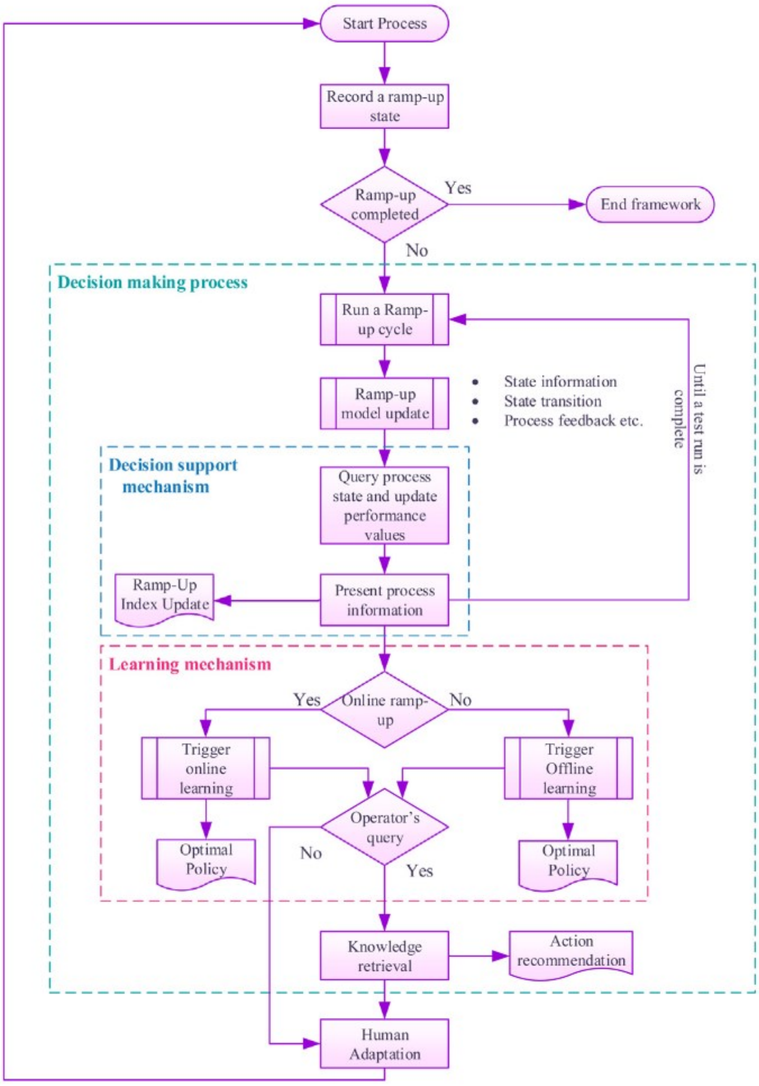

Figure 10. Decision Support System for ramp-up with learning effect (from Doltsinis 2020).

This DSS monitors ramp-up and formalizes captured data into experience. The experiences are stored and fed to a learning model, which in turn used by the decision support mechanism to provide the operator with performance information and a proposed action for every ramp-up state. The core functionalities of the proposed DSS are analysing and learning from experiences. This supportive functionalities are enabled through capturing experience; a learning model and the decision support mechanism. The DSS was evaluated in a CPS enabled microscale assembly station. Results indicate that supporting human operators during system ramp-up with performance measures can significantly reduce both the required time and the number of steps to ramp-up completion. Providing further support by recommending the most appropriate set of ramp-up actions further reduced both the time and number of steps required for ramp-up. Additional details can be found in the original publication.

6.2 Virtual Commissioning

In this Section, an example of virtual commissioning procedure for ramp-up management in scalable production systems is presented. The example is taken from Kampker (2021). Virtual commissioning speeds up the commissioning process by allowing for the pre-setting up of production systems in a simulation environment. This approach, among other things, involves early development and validation of programmable logic controllers through simulation. With the completion of the model, basic kinematics of the production system can be evaluated to detect any collisions or design faults. It is important that the Virtual Commissioning model is well aligned to the signals from the real process. Hence in the following an application showing the adaptation of the integration between Virtual Commissioning and real data is shown. The process model for connecting real data to virtual commissioning of scalable production systems involves six steps, as depicted in Figure 11. The model starts with defining the target, followed by selecting system variables, recording signal curves on the real system, updating the virtual commissioning setting, recording simulated signal curves on the model, and comparing both signal curves to formulate a recommendation for adjusting the model parameters. The target definition forms the basis of the procedure and the real plant data is recorded and analyzed, followed by adapting the virtual commissioning setting. The virtual model is then connected to the simulation, and both signal curves are compared to provide a recommendation for model parameter adaptation.

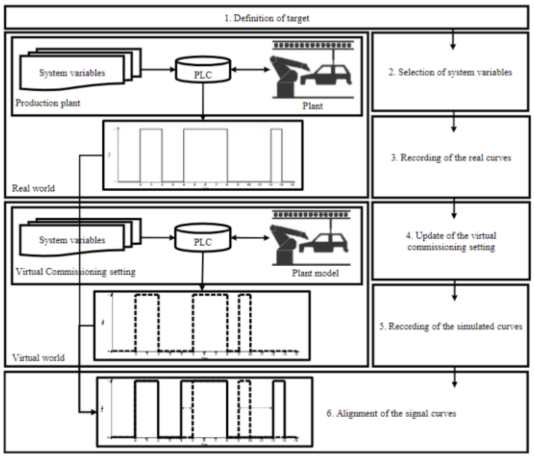

Figure 11. Methodological steps for Virtual Commissioning integration to real data (from Kampker 2021).

The process model defined here detects the deviation of the simulation model from reality regardless of the possible causes and creates the basis for bringing the deterministic model behavior closer to reality by adapting the model parameters. The process model ends with the discussion of a concrete parameter recommendation. A process model for virtual commissioning was validated using an example from the materials handling technology in electric motor production. The improvement goal was a reduction in cycle time and the scope was a 15-step cycle within the selected material handling process. 14 meaningful signals were recorded and an average cycle of 23.2 seconds was formed from three repetitions. The virtual simulation model was updated by exchanging certain module components and adjusting discrepancies in size and position, as it can be noticed in Fig. 12. The virtual cycle time was 17.5 seconds, roughly 75% of the real runtime. Further research found an average deviation of 4.1 seconds, with the simulation model being ahead of reality when not considering the overall duration.

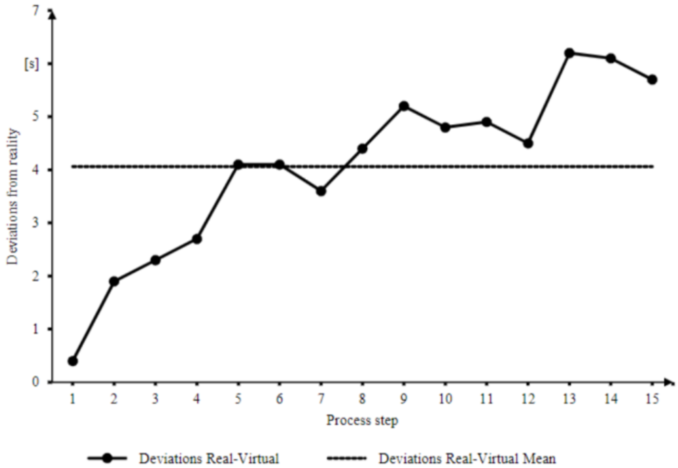

Figure 12. Deviations of VC model from real data (from Kampker 2021).

This case study shows that the implementation of VC can be used to proactively reduce the system cycle time before even going into regime production. As a consequence, VC can be considered as one of the key enabling technologies for productivity ramp-up.

7 Research directions

In this Section, possible future research directions to extend and deepen the knowledge of decision-making problems in productivity ramp-up of modern manufacturing systems are provided.

Section 2 has shown that root-causes for productivity ramp-up are manifold and descend from various sources, both organizational and technological. As a consequence, also decision-making for productivity ramp-up shall address technological and organizational strategies. As reviewed in Section 3, current research has been focusing separately on enabling technologies for reducing ramp-up, as Virtual Commissioning and plug-and-produce systems (Ugarte 2022), configuration and reconfiguration optimization according to target production mix and production volumes (Magnanini 2022), novel manufacturing technologies for matrix-based production systems (Stricker 2021) and line-less manufacturing (Göppert, 2021), as well as analysis on the key importance of human aspect for ramp-up, by means of learning aspects and workforce management and dedicated decision-support systems (Doltsinis 2020).

Within the concept of productivity ramp-up of future manufacturing systems, some research areas can be identified.

Starting from the relation between products, processes and resulting manufacturing system, the integration between automation and cognitive models may provide interesting fields of research and applications for self-adjusting production systems, that automatically identify the most suitable decisions in order to minimize or even eliminate the ramp-up. With this respect, the necessary tools that a researcher should adopt range from the latest technological innovations in reconfigurable manufacturing, to evolutionary machine learning techniques.

Moreover, when considering an evolving manufacturing system during its life-cycle, only few examples of System Digital Twins can be actually found in literature, and their integration into optimization algorithms to proactively anticipate ramp-up issues is a research area not yet fully explored. This is coupled with the important topic related to the human aspect, which is at the foundation of Industry5.0. Indeed, decision-making for minimizing the productivity ramp-up should also account for the relevance of the workforce, its training, evolution and collaboration with existing technologies. With this respect, the ramp-up and therefore reconfiguration of manufacturing systems characterized by hybrid automation has not reached its full potential yet.

Additionally, when it comes to enabling technologies, cyber-physical approaches as virtual commissioning and plug-and-produce systems may benefit from further research, especially when it comes to applications that do not relate to discrete manufacturing, as for instance in continuous processes.

Given its importance and fundamental role, several promising research avenues can be mentioned to keep up with cutting-edge technologies and global circumstances, extending the concept of productivity ramp-up to integrate services and logistics in order to address global customers (Verhaelen 2023).

For instance, COVID 19 crisis uncovered several urgent challenges in manufacturing such as the need for quick production ramp-up of medical equipment to keep-up with the pressure on healthcare sector (Ahmad et al., 2020; Das, 2020). These challenges involve the ramp-up of the production of goods (e.g. masks, grocery) and services (e.g. healthcare services, maintenance services) (Nazir et al., 2020). Yet, ramp-up in service domain is even more critical than in product domain (Heraud et al., 2022). Service intrinsic characteristics requires further research to address service ramp-up projects (Akkermans et al., 2019; Lenfle & Midler, 2009). For example, service delivery and production, and therefore ramp-up, occur simultaneously while mere product ramp-up process is conducted prior to its delivery. In this sense service ramp-up is more critical as any failure during the ramp-up process is visible to customers. In addition, as service operation involves several actors, the ramp-up process needs to be coordinated at a value network level (Cavalieri & Pezzotta, 2012; Maull et al., 2012; Medini

& Boucher, 2016). Under these circumstances, it is important to pinpoint service ramp-up intricacies as well as mutual influences between product and service. This will support more efficient planning and implementation of ramp-up projects through proper requirements identification and scope definition.

Furthermore, within VUCA environments, in order to improve ramp-up performance, i.e. time-to-market, time-to-volume, time-to-quality, time-to-cost, it is important to carefully build, integrate and share knowledge across ramp-up projects. This requires, for instance, identifying mechanisms for transforming individual know-how and experience into explicit and sharable knowledge (Riffi-Maher & Medini, 2021). Moreover, it is important to support continuous learning and improvement during fast-paced and rapidly changing ramp-up projects' environments. An efficient exploitation of information and a corporate knowledge management requires organized coordination and collaborative learning between several stakeholders within and beyond the company (Yeleneva et al., 2018). Furthermore, agile methods exhibit a high potential to deal with the uncertainty and lack of information underlying ramp-up projects. Therefore, they are a good alternative to mere plan-driven methods. This orientation started to gain interest in the particular domain of ramp-up culminating so far at guidelines or recommendations for iteratively conducting ramp-ups (Bergs et al., 2021; Heraud et al., 2023). This is likely to enhance customer integration, unpredicted development efforts and omit development/design freeze. Yet, it is still important to assess data reliability and combine data from several sources during ramp-up projects to support informed decisions.

Reaping the benefits of effective knowledge management and agile ramp-up management is also dependent on the supporting information system. This latter can even be seen as the foundation for successful ramp-up projects. The ramp-up process involves multidisciplinary teams and various components of the corporate information system such as Product Data Management and Enterprise Resource Planning. Integration and automated data migration are then important (Surbier et al., 2014), since models are usually not interpreted in the same way among these components. Industry 4.0 design principles and enabling technologies such as Cyber-Physical Systems are expected to enable a leap in achieving agility within information systems (Medini, 2022; Schmitt et al., 2018). Further empirical research is needed to gain insights into (best) practices and guide the theoretical developments in this area.

To conclude, the challenges highlighted by the analysis of state of the art in Section 3, as well as methodologies shown in Sections 4 and 5, together with case studies from Section 6, show that the manifold root-causes for productivity ramp-up are quite intertwined, hence future disruptive research areas should address how key enabling technologies, evolutionary algorithms, advanced software solutions, attention to the human intuition and workforce management can be jointly considered for resilient and sustainable manufacturing systems.

8 Conclusion

Productivity ramp-up has gained momentum as research problem. The literature is still sparse and problems related to productivity ramp-up are articulated under different definitions in state of the art. Moreover, technological and digital solutions allow for integrated approaches as decision-support systems to improve different aspects of productivity ramp-up, starting with design decisions aiming to reduce the reconfiguration and recurrent ramp-up time. It can be also noticed that during ramp-up many problems may arise, including sourcing issues, need for learning for the workforce, and planning of the right improvement actions with respect to productivity and available data.

To conclude, research shows a great interest towards problems related to ramp-up, as the manufacturing global context is not only dynamic, but also extremely uncertain. Moreover, ramp-up is by definition a non-sustainable phase in the life-cycle of manufacturing systems. Indeed, during ramp-up, resources are not performing at their best, or are prevented from being fully operational and optimized due to unknown conditions, that can be tracked to multiple sources, as technology adaptability and integration, software connections and performance, workforce learning. Decisions related to the identification, management and optimization of these actions in complex manufacturing systems require data and models, as well as suitable decision-support methods integrating optimization algorithms. Many challenges are still ahead, tackling the identification of root-cause for ramp-up, the co-evolution of product-process-system in order to avoid non-sustainable phases of manufacturing system's life-cycle, as ramp-up is, and novel key enabling technologies to ease productivity ramp-up. Hence, the objective of minimizing the ramp-up effect is strategical for the sustainable development of manufacturing.

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