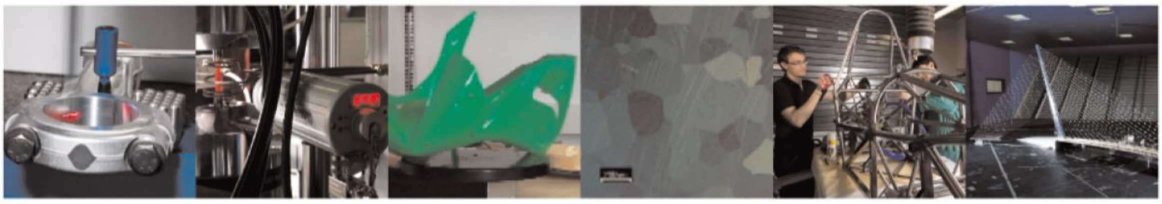

Production quality improvement during manufacturing systems ramp-up

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Production Quality Improvement During Manufacturing Systems Ramp-up

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Abstract: In the current manufacturing context, characterized by short product life-cycles, large product variety, product customization and short innovation cycles, achieving target production quality performance is challenging, especially due to the frequent ramp-up phases the system undergoes along its life-cycle. Available production quality methods focus on high-volume productions and long-term system performance, while they lose effectiveness during the system ramp-up, where instability and unknown disturbances affect the system dynamics. This paper proposes a reference framework for improving production quality performance during the system ramp-up phase. Two strategies for properly dealing with this problem are discussed, consisting in anticipating ramp-up problems during the design phase and performing continuous improvement of production quality performance measures during the system ramp-up. The most effective approaches following these strategies are revised and future research directions in this new research area are drawn.

Keywords: Production Quality, Manufacturing Systems, Ramp-up.

1. Introduction, motivation and objectives

Manufacturing companies are continuously facing the challenge of operating their manufacturing processes and systems in order to deliver the required production rates of high quality products while minimizing the use of resources. In response to these needs, "*Production Quality*" was recently formulated as the discipline that combines quality, production logistics, and maintenance methods and tools to maintain the throughput and the service level of conforming parts under control and to improve them over time, with minimal waste of resources and materials [1]. Several emerging market trends have considerably reshaped the boundaries within which quality, production logistics and maintenance aspects interact.
The increasing product variety and customization [2] 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 of continuous adaptations of the system configuration to integrate these technological enablers. Furthermore, reconfigurability [3], changeability [4] and co-evolution [5] are nowadays highly accepted paradigms in industry, enabling a strong coordination between the dynamics of the system life cycle and the dynamics of the product and process life cycles. As a consequence, manufacturing systems are continuously evolving during their life-cycles.
After a reconfiguration, the system usually fails in delivering the required production quality performance, due to the increased production of defective items and unexpected machine failures caused by the implemented changes at physical or control level. Time-consuming and expensive interventions are needed to understand and react to these disturbances. This phase is usually denoted as the *ramp-up phase* of a manufacturing system, commonly defined as the period from the production of the first item after a system reconfiguration until the achievement of the specified target output rate. The length of this period is referred to as the "*ramp-up-time*" [6] or "*time-to-volume*" [7], and it is characterized by an increasing output production rate and quality yield [8]. For example, it was shown that in the automotive industry the ramp-up phase after a new model introduction can typically last between 20 and 30 weeks and can contribute to substantial extra production costs due to capacity and quality losses as well as personnel extra-cost [9], [10]. During the ramp-up phase, disturbances that impact both productivity [11] and product quality [12] are faced with a higher frequency, due to the system's instability [13] after the process changes and system reconfigurations. The major problems that need to be addressed during the ramp-up phase include the adjustment of the production system capability and capacity [14], the reliability of manufacturing equipment to meet the target production rate [15], the understanding of the new process behavior [16], [17], and the improvement of product quality [18], [19].
If a system evolves with fast dynamics, new challenges arise for production quality. In particular, the long-term production quality performance of the system becomes less important, while production quality performance during system ramp-up assumes fundamental relevance. Traditional Six-Sigma and just-in-time methods have proved effective in stable, large volume, production contexts, since they rely on the statistical analysis of large data samples collected in stable process conditions. However, they are not effective for such dynamically changing

contexts. At the same time, the industry 4.0 revolution has provided capability to exploit emerging digital technologies for supporting a faster transition to target production quality performance level during the system ramp-up phase.
This paper discusses and formalizes the problem of improving production quality during the ramp-up phase of manufacturing systems to achieve a fast convergence to the desired production targets, with minimal production and resource losses. It revises the most recent methods and tools in this field and highlights open research challenges that should be addressed for achieving a systematic approach towards ramp-up management.
The paper is structured as follows. In the next section, a new reference framework for approaching the production quality improvement problem during the system ramp-up phase is proposed. In section 3, the most relevant and mature approaches for targeting the considered problem are revised. In section 4, the key emerging technologies for ramp-up reduction are discussed and future research needs are highlighted in section 5.

2. Reference framework

In this section, specific definitions setting the boundaries of the ramp-up management problem are provided and a reference framework, identifying proper strategies for addressing this problem, is discussed.

3.1 *Effective throughput curve during the system ramp-up*

According to the production quality theory, the most significant performance measure in manufacturing systems, synthetizing the joint effect of quality, production and maintenance control methods, is the system effective throughput, denoted as TH^{Eff}, defined as the production rate of conforming products delivered by the system. It can be expressed as the product of the system total throughput, i.e. the total number of parts delivered by the system in a given time unit, and the system yield, defined as the fraction of conforming items delivered by the system.
In line with this view, the ramp-up time can be defined as the time span between the production of the first part after a system reconfiguration and the stable production of parts at the target effective throughput level. 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 usually not achieved, since several causes for production losses are observed. This phenomenon is represented in Figure 1. The horizontal red line represents the target effective throughput, TH^{Target}, of the system after a reconfiguration that ends at time $t=0$. The blue curve represents the average effective production rate curve observed in real systems after a reconfiguration. For example, it can be considered as the average daily, or single shift, throughput curve. The ramp up time, t_{ramp}, indicated as a blue tick on the horizontal axis, is the time the system requires to reach the target effective production rate. The red area indicates the cumulative throughput loss, TH^{Loss}, observed during the ramp-up phase. It can be estimated as follows:

$$TH^{\text{Loss}} = \int_{t=0}^{t=t_{ramp}} \left(TH^{\text{Target}} - TH^{\text{Eff}}(t) \right) dt \qquad (1)$$

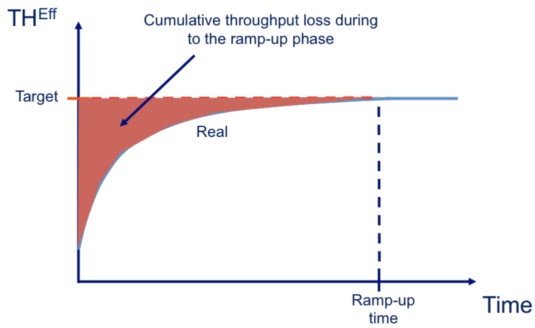

Figure 1: Cumulative effective throughput loss during ramp-up.

The effective throughput loss problem is even more significant in the presence of multiple reconfigurations of the system. This case is represented in Figure 2. 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 Figure 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. This topic is investigated in the next section.

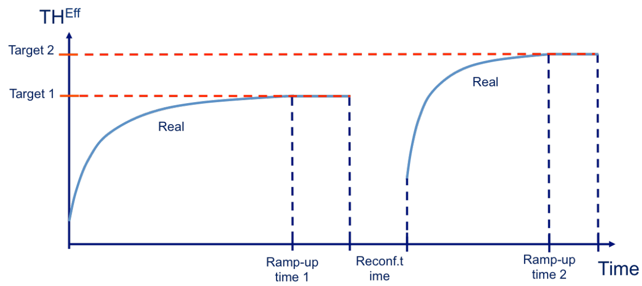

Figure 2: System ramp-up times along multiple reconfigurations.

2.1 *Causes for effective throughput loss during system ramp-up*

The causes for effective throughput losses observed during the ramp-up phase are usually related to a *mismatch* among system design assumptions and actual verified conditions. In other words, the incomplete knowledge of the system behavior exploited during the system design phase may cause the system to behave differently once the reconfiguration is implemented, leading to the need of acquiring more knowledge to bridge this knowledge gap and implement countermeasures. This mismatch is generated by *disturbances* [9] that are defined as unexpected events affecting the dynamics of the system during the ramp-up phase, making it different from the known dynamics of the system, considered during the system design phase [20].
Such causes can be then classified in two categories, namely *internal* and *external* causes. While internal causes are related to a mismatch originated within the system, external causes are due to disturbances originated outside the system boundary that have an indirect effect on the system behavior. Examples of typical

internal causes for effective throughput losses during the ramp-up phase are related to:

- *Equipment behavior:* this cause is especially relevant when the reconfiguration entails the integration of a new equipment. During the design phase it is usual to consider nominal equipment conditions and information about standard failure modes and periodic maintenance actions, typically provided by the equipment manufacturer. However, more causes for machine failures and defect generation may emerge once the equipment is integrated in the real system. For example, unexpected jammings, collisions, excessive frictions, component deformations, vibrations can be experienced.
- *Behavior emerging from the integration of multiple resources in the system:* several types of disturbances may emerge by the integration of resources in a system, that are very difficult to capture during the design phase. For example, specific defect propagation mechanisms can be observed along the system stages, due to unknown inter-stage correlations. Moreover, variations in process times can be observed, that translate into propagation of blocking and starvation. Furthermore, vibrations generated within a process can propagate to other neighboring machines, undermining their process stability.
- *Part variability:* process planning and parameters selection is usually conducted considering nominal part geometries. However, in real settings, parts flowing in the system are characterized by variability that may lead to problems in part fixing and centering, excessive tool wear, poor robot gripping capabilities, etc.
- *Poor design of the system*: the lack of knowledge about degraded states and real equipment conditions may cause system design decision to prove sub-performing. For example, poor allocation or positioning of sensors, poor allocation of buffers, poor design of fixtures and clamping devices, poor design of grippers are typical consequences.
- *Poor design of the plant control system*: the designed system control logics and software may prove to work poorly while integrated within the real system, due to wrong specifications or unexpected system states.
- *Human errors and slow learning processes*: human operators may experience a slower learning curve than expected, resulting in excessive processing times of manual operations, excessive corrective maintenance times or imprecise inspection tasks.

Examples of external causes for effective throughput losses during the ramp-up phase are as follows:

- *Mismatch in the incoming raw materials conditions:* when designing a system it is common to consider nominal conditions of incoming raw materials and semi-finished part supplies. However, although within tolerances, incoming raw parts are affected by variability, both within a supplier and between different suppliers. Such variability is difficult to predict and may alter the planned process conditions, resulting in unexpected defective part rates.
- *Mismatch in plant service conditions (energy supply, aspiration system, lighting system, etc.):* perfect stability of plant service supply is usually considered while designing a system. However, in the real settings plant services are affected by disturbances in the external network that creates instability that may affect the machine behavior.
- *Mismatch due to cultural and organizational behavior:* The reaction of the organization and the workers to a reconfiguration of the system is very difficult to predict. Problems may arise from the lack of specific skills, unformalized company procedures for executing specific tasks, or unbalanced personnel allocation to different operations in the reconfigured system.

The ultimate effects of these causes for mismatch are unexpected quality problems, low machine availabilities due to unexpected machine failures, and high maintenance costs.

2.2 *Strategies for reducing effective throughput losses during the system ramp-up*

Given the causes for production quality losses discussed in the previous section, the key question that this paper addresses is "How can the design, management and control of manufacturing systems be improved to reduce the effective throughput losses due to the system ramp-up?". With the objective to reduce the gap and the subsequent mismatch between design knowledge and the verified real system behavior, two major strategies for ramp-up reduction can be identified:

Strategy 1: to anticipate the potential disturbances arising in the ramp-up phase during the design phase. This strategy consists in capturing potential problems occurring in the ramp-up phase already in the design phase by, for example, (i) modeling potential failures and disruptions of machines, (ii) modeling real variable parts instead of ideal parts, (iii) provide redundancy and robustness to the designed system, (iv) capturing the effect of the control logics on the system performance.

Strategy 2: to acquire new knowledge about the actual system behavior, through data gathering and analysis, once the reconfigured system is implemented, and to perform system improvement by exploiting this information.

Both strategies may contribute to the reduction of the effective throughput losses during the ramp-up time, although the effect of the application of these two strategies is significantly different. Referring to Figure 3, the application of strategy 1 contributes 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. 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. The application of strategy 2 instead contributes to the reduction of the throughput losses by shortening the ramp-up time. Indeed, this strategy provides capability for a fast identification and removal of system bottlenecks. Since both strategies have a cost, either related to a more complex design problem (strategy 1) or to the availability of a data gathering system (strategy 2), and require specific support models and tools to be implemented, a combination between the two strategies may result to be an effective approach for ramp-up management.

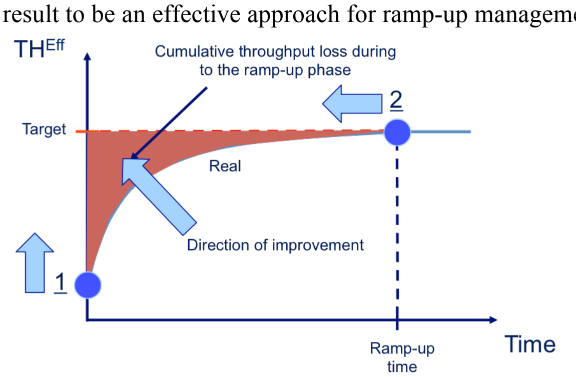

Figure 3: Effect of ramp-up reduction strategies.

In the remainder of this paper, the existing contributions, models and methods addressing these two strategies are revised with the objective to provide an overview and guidelines for practitioners and researchers approaching this problem.

3. Ramp-up management methods

3.1 *Ramp-up considerations during product and system design*

The design of complex manufacturing systems requires a long iterative procedure where several design changes are implemented and validated before the final solution is delivered. This process is constrained by strict time and monetary budgets that further undermine the ability to refine the solution in view of shorter ramp-up phase. As a consequence, a typical decision is to delay detailed system fine tunings to the installation and ramp-up phase. However, the increased availability of digital manufacturing tools has provided new opportunities for anticipating the consideration of ramp-up related issues during the system design process, without significantly extending the design time and the related costs. This is usually achieved by integrating specific effective throughput loss causes during the ramp-up phase within the manufacturing system models adopted to support the system design and redesign phases.

A generalized classification of works targeting ramp-up management during the design phase and later reconfiguration phases is provided in [21]. Most of the available approaches focus on specific throughput loss causes during the ramp-up phase, in isolation. Among the methods considering internal causes for throughput losses, a wide set of contributions concentrates on the effect of equipment behavior on the system ramp-up, thus leading to a selection of equipment for system reconfigurations with favorable ramp-up conditions. For example, in [22], a combined analytical model and hybrid simulation environment is adopted to predict the expected ramp-up profile derived from the integration of new production technologies into an existing production system. The method can be used to evaluate different alternative configurations, not only with respect to the attainable target effective throughput, but also with respect to the ramp-up duration. In [24], a capacity planning and machine selection problem along multiple system reconfigurations is considered that directly takes into account a simplified, linear, ramp-up model and the related costs with the objective to evaluate the best system capacity adjustment trajectories to cope with evolving production requirements. The analysis is based on the analytical solution of a Markov decision problem. Quality related aspects are not taken into account. The results show that sub-performing system reconfigurations can be selected if the ramp-up costs are neglected. A similar problem was formulated in [23] and solved through a heuristic approach to find the optimal reconfiguration trajectory along multiple reconfiguration paths.

Other contributions showed that specific system architectures feature improved capabilities to cause short ramp-up times, by design [25], [24]. For example, in [26] the effect of adopting modular and hybrid system architectures on the system ramp-up is discussed and a generic approach for achieving a scalable production system characterized by short ramp-ups after configuration changes is proposed.

The anticipation of machine failures and system integration issues in the design phase has also been largely investigated. This research area provides integrated analytic models, implemented within digital tools, for the analysis of the effective throughput in multi-stage systems, directly considering the interaction between quality, logistics and maintenance aspects. Among these, in [28] the authors developed a model of a multi-stage asynchronous serial line where machines are subject to failures and degradation. In operational states, the production of defective items is considered. Production control, preventive maintenance, and quality control policies can also be modelled in the same framework. The proposed analytic dynamic model, based on the decomposition of the entire system into sub-systems that are easy to analyze with exact technique, makes it possible to predict the system effective throughput under specific configurations. A recent review of this class of models can be found in [1]. These methods can be used as digital tools to test different configurations with respect to the predicted production quality performance, in the early stage system design phase. They enable to investigate the robustness of the designed system with respect to various causes for disturbances affecting the effective throughput of the system. Most of these approaches consider perfect knowledge about stochastic machine failures and repair event frequencies and durations. However, these data are usually emerging from the system behavior once the system is installed. In [28], the effect of uncertain reliability parameters estimates on the subsequent system design decisions is investigated. The authors show that, in order to cope with this uncertain information, a robust system design should be performed, resulting in a more-expensive over-capacitated configuration that can better cope with the ramp-up phase.

Other works propose frameworks and methodologies that consider the production ramp-up already during the early stages of the New Product Introduction (NPI) process. In these works, the main goal is to support a fast introduction of new products and reduce unexpected and expensive delays in highly competitive industries, such as the automotive sector. The definition of ramp-up considered in these works slightly differs from the definition given in this paper. In this case, the ramp-up is considered as the transition from the completed product development to the volume production. In [29] the authors highlight the need for early consideration of the ramp-up phase in the development of complex products. A systematic approach supporting the early identification and minimization of possible ramp-up risks is presented. In [30] a quantitative methodology to predict critical risk factors and their potential effect on the extension of the ramp-up in the NPI process is provided. The experimental validation of the approach shows that good agreement among the predicted effects and the observed effects is met, thus making the approach a practical tool for anticipating ramp-up extension risks.

Other strategies study the impacts on ramp-up by considering the joint co-creation of product and system designs into an integrated framework that explicitly considers the interaction between the two domains ([18], [31]). For example, in [32] the adoption of factory standards and standardized product architectures is proposed as a key step to mitigate disturbances arising due to ramp-up. Some approaches extend this concept to a broader perspective by jointly considering the product concept, the product development process, the logistics system, the manufacturing capability and the external environment within the same framework [33].

A concrete example of an approach anticipating multiple ramp-up risk factors in the design phase is provided in [34], where a complete software toolkit to support the integrated system and workstation design as well as process planning and control, by jointly considering quality and reliability issues, was developed. The aim is to support the NPI phase caused by a transition from Resistance Spot Welding (RSW) to Remote Laser Welding (RLW) technologies in Body In White sheet metal joining in the automotive industry. The approach is based on the results achieved within the RLW Navigator EU FP7 Project. At system level, a plant configuration and optimization tool is developed supporting machine selection, buffer allocation and layout planning by taking into account machine failures. At workstation level, a robot simulation and off-line programming software is developed to determine the optimal configuration and operational conditions of the RLW station to process all joints (also called stitches) with minimal cycle time, respecting physical constraints. At process planning level, an engineering software for robust design of the door fixture, under non-ideal part geometries, modelled as multiple part variation modes, is developed. At process level, a meta-model for supporting laser parameter selection for feasible stich welding is proposed. These tools are integrated into an interoperable digital factory workflow, called the RLW Navigator, validated through application to a real case study in JLR UK. This systematic coordination of software modules across different stages of NPI enables 'right-first-time' solution capability, decreased commissioning time and cost, shorter design time, improved design robustness, and knowledge re-use, by which the overall NPI process can be accelerated. Overall, the proposed approach proved to enable a considerable reduction in the NPI process (-30%) together with an improved system feasibility before the commissioning, which was predicted to shorten ramp-up times of about 20%.

Some approaches propose methodologies that investigate the impact of external causes on the ramp-up length, for example at supply chain [35] and production network level [36]. These approaches take a product-centric perspective and investigate whether supplier involvement in a new product development process can produce significant improvements in financial returns and ramp-up performance. Under situations where there is a big misfit between the existing product and the new product variants that lead to substantial modifications on the existing manufacturing system, a significant instability in the whole value creation processes can be originated. In these cases, the methods assess the feasible set of product variants that can mitigate the negative effects of such instability [37]. In [12] the research conducted by the authors revealed that leading Japanese manufacturing firms in the high-tech electronic industry were utilizing their collaborative inter-firm manufacturing supply network to minimize time-to-volume as part of the total effort in speeding up NPI to market. The provided figures show that, with the inter-firm approach, the average in-line defects percentage was lowered from 50% at the production start down to less than 4% in about 50 days, also considerably reducing the variability of the effective throughput in this transition.

The problem of integrating the control system design and verification within the system design phase has also been considered. These approaches aim at providing capability to perform a "virtual commissioning" of the manufacturing system, testing potential control related problems before the real system installation, thus reducing ramp-up and commissioning costs. Without virtual commissioning, a manufacturing system will have to be stabilized solely by real commissioning with real plants and real controllers, which is very expensive and time consuming. This aspect is emerging as particularly critical due to the increasing complexity of production system architectures. The typical approach to control software development and validation is as follows:

- *System definition:* the process to be automated is described, and the objectives of the automation system are defined;
- *Control system specification:* the tasks and the essential functions of the supervision and control system are defined;
- *Control system design:* the supervision and control functions are designed through a suitable reference model;
- *Control system implementation:* the control code is generated;
- *Control system verification:* the designed control functions are verified against the requirements.

The approach of virtual commissioning for control system verification entails the use of closed-loop simulation techniques, in particular "hardware-in-the-loop" simulation, [38]. In order to realize "hardware-in-the-loop" simulations it is necessary to design a real controller (control system area) that emulates the automation system control functionalities and that is connected to a second system (process simulator area) that simulates the physical behavior of the real plant. Another strategy is to apply the so called "reality-in-the-loop" approach, where a real factory is coupled with a virtual controller. In particular, if a small scale plant is adopted in the testing phase, this approach allows using the real communication protocols whose functionalities are not easily modelled in a software simulator, without extensive tests in the large scale manufacturing facility. A recent review of virtual commissioning approaches can be found in [39]. It was proved that virtual commissioning approaches could lead to a reduction of real commissioning time of 75%, resulting from enhanced quality of the manufacturing system at the start of real commissioning [40].

3.2 *Continuous improvement during the ramp-up phase*

Once the design phase is completed and the ramp-up phase is initiated, methods and tools to gather information about the actual system behavior and perform root cause identification, error budgeting and system improvement can be implemented in order to reach the target effective throughput level. At this stage, more detailed information about the system behavior is available, that could not be precisely known in the design phase [41]. Empirical studies of real manufacturing ramp-up cases in automotive ([9], [8]), aeronautics [42], and electronics ([33] [43]) industries show that significant benefits can be achieved from an efficient application of ramp-up management methods in this critical phase. The methods developed to this purpose vary according to the specific nature of the ramp-up disturbance they tackle and the solution approaches used to quantitatively solve the problem.

A wide body of literature is dedicated to the identification and control of quality correlations in multi-stage systems, in order to improve the system yield and decrease the production of defective items. In multi-stage manufacturing processes, understanding how a defect generated in a specific process stage propagates to the next process stages and what effect this propagation has on the final product quality is a complex task. Engineering methods and advanced Multivariate Statistical Process Control (MSPC) methods have been proposed to model and monitor quality correlations in multi-stage processes. Of the engineering methods, SOVA (Stream of Variations Analysis) [44] has been proposed for assembly systems and machining process-chains. This approach is based on a state-space representation of the correlation between the product deviations at consecutive process stages whose structure is driven by engineering knowledge about the processes and whose coefficients are tuned by KPC (Key Product Characteristics) measurements at the different stages. Being based on engineering models, the number of measurements required for capturing the dynamics of defect propagations and, consequently, identifying the most important causes for deviations is usually substantially lower than statistical methods, thus making SOVA a powerful tool for ramp-up management. Applications of SOVA to optimize a single ramp-up cycle in complex multi-stage manufacturing systems, by integrating multivariate statistics, control theory and design/manufacturing knowledge into a unified framework, can be found in [18]. Usually, these approaches focus only on part variation propagation along system stages and aim at increasing the system yield, while they neglect the effect of machine failures on logistics performance at system level.

Other approaches focus on the identification and removal of disturbances related to the equipment behavior, machine failures and to the integration of resources in the system with a production oriented perspective. The typical continuous improvement loop applied by these methods is reported in Figure 4, as suggested in [45], where the application of this procedure to an engine block production line in Scania, Sweden, was proposed. According to this framework, data about the machine state sequences and failure statistics are collected in-line through the production monitoring system, during the ramp-up phase. Such data are exploited to feed state-based resource models that are integrated into an engineering model of the system, capturing the dynamics of the material flow along the stages of the modelled multi-stage system through equations that are solved by an analytic approach. Once this model is available, it can be used as a digital twin for performing model-based dynamic bottleneck identification, system reconfiguration optimization and to perform sensitivity "what-if" analysis to virtually check the effect of specific interventions on the existing system. For example, those failures having the highest impacts on the production rate of the system can be identified in order to prioritize interventions during the ramp-up phase.

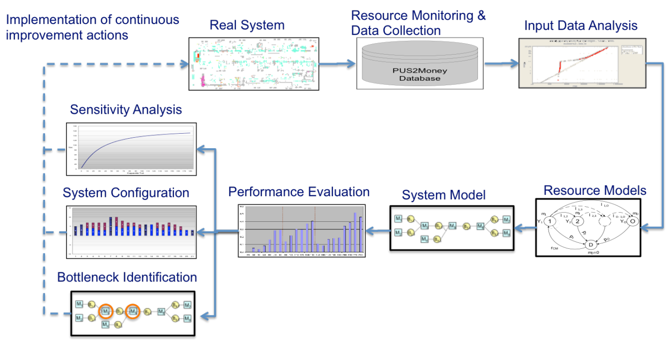

Figure 4: Continuous improvement loop during the ramp-up phase.

The application of this approach to the automotive engine block line under analysis proved that a production rate increase of about 20% could be achieved by identifying and prioritizing improvement interventions. A further extension of this approach considered action prioritization in presence of limited workforce during the ramp-up phase [46].

Other approaches focus on productivity-oriented improvements by proposing methods for data-driven dynamic bottleneck identification based on data gathered on-line during the ramp-up phase. Production logistics bottlenecks in manufacturing systems are defined as those specific resources that feature disturbances with the highest effect on the entire system total throughput. A typical phenomenon during the ramp-up phase is the non-static distribution of bottlenecks: while specific problems are tackled and get solved during the production ramp-up, bottlenecks dynamically move from one station to another. With the objective to focus improvement efforts, such as cycle time and downtime reduction, on the most important stations and disturbance causes, a reliable and constant knowledge of bottlenecks is an important asset. In [47], a purely data-driven methodology for dynamic bottleneck identification to be used on-line for continuous improvement is proposed. The method elaborates data collected from the Manufacturing Execution System (MES) and, at each time unit, detects the current bottleneck machine applying an algorithm based on state transformation. The application of this method to two real case studies showed that bottlenecks can be reliably identified after few hours of production, making the applicability of this approach to ramp-up reduction very promising. A different approach to on-line short-term bottleneck identification was proposed in [48], where the authors proposed to observe blocking and starvation probabilities and buffer levels records to infer the time-dependent location of the bottleneck. The method was validated against simulation and analytical methods and proved effective for a quick identification of bottleneck stations. Furthermore, in [49] a systematic method to identify the causes of permanent production losses in manufacturing systems based on a data-driven model that describes the production dynamics is proposed. This method can be applied to the bottleneck identification problem and can also be used to identify the impact of specific disruption types for which sensor data are available. With the development of computer technology and the increasing amounts of data collected by MES and distributed sensor networks, data-driven algorithms using the online production data present a new way to perform ramp-up management in an effective and highly reactive way.

Other methods for ramp-up management focus on the effect of operators' training and learning on production quality performance [8]. Some methods model the learning process in the form of experiments executed on the system during the system ramp-up to gather specific knowledge on the resource behavior. Such experiments reduce the production rate in the short run. Therefore, a trade-off between experimental effort and performance improvement needs to be solved. In [6], the authors proposed the interesting concept of using "gamification" for increasing the learning rate of workers in assembly lines during the system ramp-up. Similarly, in [50] a game-based simulation environment is used to train managers and workers in view of a more effective ramp-up management. In [51] augmented reality is proposed as a technology for supporting engineers during control system verification within the ramp-up cycle and for personnel training. Through this technology, faults in the installation and the control software can be easily identified, thus reducing the control commissioning time. Since training the employees is one of the most important and cost-intensive processes in ramp-up, these approaches can be highly beneficial, especially in contexts with substantial manual work content.

4. Enabling technologies for ramp-up reduction

Emerging Key Enabling Technologies (KETs), such as in-line data gathering solutions, data storage and communication standards, data analytics tools and digital manufacturing technologies offer new opportunities for ramp-up management in view of production quality performance targets, also in complex production environments. These technologies, listed in Figure 5, are increasingly becoming integral part of modern production systems, also due to the advent of the "Industry 4.0" paradigm. However, a problem-driven cross-KET approach should be envisaged in order to select and identify the proper technology mix to support the ramp-up management problem on a case-by-case basis.

In line with this vision, 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 [52]. The key architecture of the system proposed in the project is represented in Figure 6. 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 will be 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.

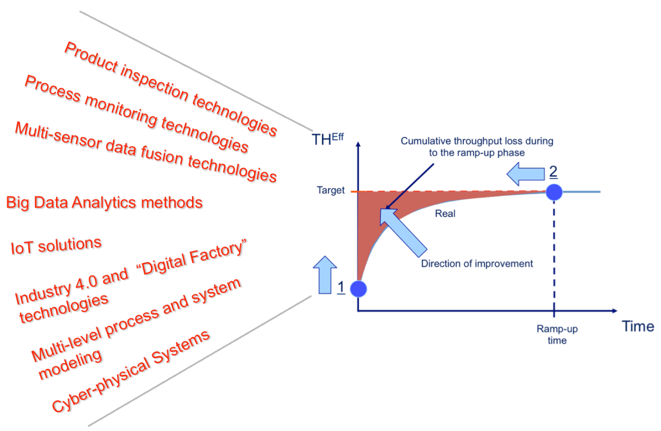

Figure 5: Relevance of a cross-KETs approach for production quality ramp-up reduction.

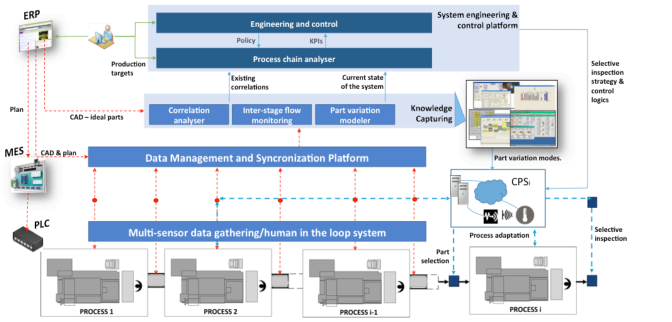

Figure 6: Reference architecture for short-run production quality improvement proposed within the ForZDM EU project [58].

If these key enabling technologies are properly integrated with a cross-KETs approach, new solutions can be designed and implemented at shop floor level, to efficiently support systemic ramp-up management methods. These potential innovations, which constitute opportunities for future research, are discussed in the next section, focusing both on design methods and continuous improvement methods during the ramp-up phase.

5. Future Research Challenges

Robust system design methods. Embedding uncertainty in the parameters considered during the system design phase is a potentially good strategy to anticipate ramp-up disturbances and to provide robustness to the system design. However, it usually results in over-capacitated resilient systems, which lead to higher system implementation costs. Therefore, a trade-off between robustness level and ramp-up risks is generated. Developing design methods for cost-aware system robustness analysis in view of ramp-up risks would be advisable to enable practitioners to compare different robustness levels and decide the best configuration, embedding the ramp-up costs in the problem.

Multi-method, multi-level and multi-physics digital manufacturing system modelling. As highlighted in section 2, the causes for ramp-up extensions are several and affect the system production quality performance through different mechanisms. Nowadays, the computational performance of modern processors as well as the achievements in parallel and high-performance computing have enabled to set-up effective multi-level, multi-method and multi-physics digital modelling and simulation environments, where several aspects contributing to the dynamics of complex systems can be analyzed in integrated workflows. However, such approaches are rarely adopted in manufacturing systems engineering, although they would be particularly suitable, especially for complex design problems where multiple domains interact to determine the quality of the proposed solution. For example, combining multi-body simulation, able to model the contact forces among rigid bodies composing a system, with discrete event material flow simulation would lead to a better understanding of collisions, frictions, and contacts among system equipment, moving parts and fixtures or transportation modules, enabling to anticipate currently neglected ramp-up disturbances already in the design phase.

Cyber-Physical Systems. A very promising area of research in the ramp-up management literature is looking at exploiting the capabilities of cyber-physical systems to improve data-analytics, learning and self-adjustment capabilities of the system, towards a production quality improvement loop [53]. Cyber Physical Systems (CPSs) are usually defined as systems integrating computation and physical actuation capabilities [54]. In CPSs, embedded computers and networks monitor and control physical processes, usually with feedback loops, where physical processes affect computations and vice versa [55]. Innovative applications of CPSs for improving manufacturing efficiency and responding to emerging industrial problems are attracting the interest of both industries and researchers [56]. Given the continuous occurrence of new scenarios during the ramp-up phase, approaches for self-directed systems capable of learning and adapting their behavior depending on the observed conditions and target goals are the new frontiers of this research. A first work in this direction was proposed in [56] where the authors presented a concept of self-learning CPS agent, based on reinforcement learning, and demonstrated it in three ramp-up management contexts. Moreover, in [57] a CPS-based solution was implemented in a electric-drive assembly line in order to smooth the propagation of defective items along the stages of the multi-stage assembly line and meet an overall improvement of effective throughput of about 18%. Since these approaches are promising and suitable for on-line implementation, more effort should be devoted to the development of this area in view of production quality performance improvement during the ramp-up phase.

Knowledge transfer methods among subsequent system reconfigurations and ramp-ups. Although the discussion about the use of big data analytics in manufacturing is on going within the scientific and industrial community ([58], [59]), the application of these techniques in real manufacturing contexts is still very limited. Since one of the key features of the ramp-up management problem is the need to address a limited number of disturbances of known type leading to specific and unique problems, which differ at each reconfiguration period, data analytics techniques appear as very promising approaches in this area. However, if these techniques are applied independently at each ramp-up management cycle, a large set of data may be needed before reliable tools for root cause analysis and improvement prioritization can be managed. A good strategy to apply data analytics in the ramp-up management context seems to be the following: (i) categorize the typical disturbance causes encountered during the ramp-up phase, (ii) store data about improvement actions and system responses along multiple ramp-up cycles, (iii) apply data analytics and learning algorithms to generate a decision support engine based on knowledge re-use along different ramp-up management cycles. This approach is expected to provide a learning effect along system reconfigurations that can potentially result in significant cost and time savings, after few ramp-up management cycles are carried out.

Improve learning capabilities by heterogeneous data gathering and analysis. Available quality monitoring, control and improvement techniques are usually based either on product quality characteristics data, gathered by product inspection devices, process variables' data, gathered by process sensors, or a combination of both, in the most advanced cases. However, as proposed within the ForZDM project approach, multiple distributed data sources can nowadays be exploited to gather heterogeneous process, part quality, machine state, part location and human-feedback data on-line at shop floor level. By using these data with more advanced data analytics and learning algorithms, additional knowledge can be acquired on the system behavior that can be useful for system improvement during the ramp-up phase. For example, by modelling the effect of a degraded machine state on the variability of a part quality feature processed by that machine, an effective and responsive yield improvement action can be implemented. For instance, the time the machine spends in that degraded state can be reduced through the implementation of preventive maintenance. Similar examples motivate the adoption of a more holistic approach to data correlation analysis for production quality improvement during the ramp-up phase.

Reduce variability of effective production rate. While most of the methods for production quality improvement focus on the reduction of the ramp-up time, related to the average effective throughput production rate, very little attention has been dedicated to the reduction of the throughput variability during the ramp-up phase. However, as shown in Figure 7, elaborated from a real ramp-up profile of an automated assembly system in the furniture industry, the variability of the throughput during the ramp-up is significant.

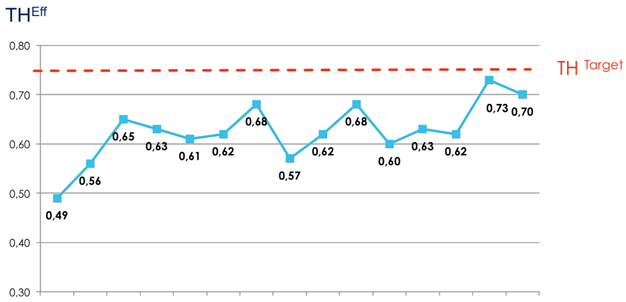

Figure 7: Throughput profile showing high variability during the ramp-up phase.

Along the ramp-up, high throughput fluctuations are negative as structural throughput improvement trends are hidden by the throughput variability and over-adjustments in the system behavior can be induced. Moreover, large throughput variability affects the service level and the due-time performance of the system **Errore. L'origine riferimento non è stata trovata.**. To avoid these effects, more efforts should be devoted to the mitigation of the production quality variability during the ramp-up phase, in order to reach at the same time the target effective production rate with smoothed throughput variability, as highlighted in Figure 8.

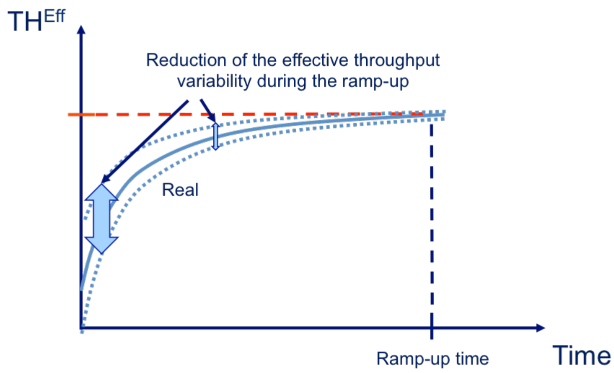

Figure 8: Reduction of effective throughput variability during the ramp-up phase.

6. Conclusion and key messages

This paper has provided a reference framework for defining strategies to improve manufacturing systems production quality performance during the ramp-up phase and has revised the available methods and tools supporting this goal. The main messages contained in the paper can be summarized as follows:

- The effective throughput is the most relevant performance measure to be improved during the ramp-up phase; it is jointly affected by quality, maintenance and production logistics decision variables
- Effective strategies to reduce ramp-up losses include (i) anticipating disturbances during the design phase and (ii) monitoring the production to react to unknown disturbances.
- Digital system and process modeling play a relevant role in ramp-up reduction, as it allows capturing and understanding complex system dynamics and phenomena.
- System reconfigurations and adaptations are additional burdens on ramp-up management, as the system is frequently in transient behavior.
- A Cross-KET approach, grounding on the most recent technologies for data gathering, modeling and analysis, should be investigated to properly address ramp-up reduction challenges in the Factory of the Future.

Future research directions are also highlighted that could support the fast transition to new ramp-up management solutions, exploiting the opportunities of the most recent industry 4.0 technologies.

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