MASTER

Measuring ramp-up performance of job shops using a real-time location system

a case study of a photonic semiconductor foundry

Smolenaars, A. (Bram)

Award date:
2022

Eindhoven University of Technology

Master thesis

Measuring ramp-up performance of job shops using a real-time location system

A case study of a photonic semiconductor foundry

Master: Manufacturing Systems Engineering
Research group: Operations Planning Accounting & Control

Student: A. Smolenaars (Abraham)
Student nr.: 1008360

Supervisors: Dr.ir. A.E. Akçay (Alp)
Prof.dr.ir. I. Adan (Ivo)
Prof.dr.ir. R.M. Dijkman (Remco)

Commissioned by:
SMART Photonics

A. Van de Geijn (André)

Eindhoven, December 9, 2022

Abstract

The shift of high-tech production companies from time-to-market to time-to-volume during the 00s put the tail-end of the so-called 'ramp-up' in a critical position. Whereas existing literature uses established (stable) production processes as use cases assessing performance on cost, quality, flexibility, and productivity, the ramp-up has other challenges. Traditionally, ramp-up stages are characterized as unstable, unpredictable, inflexible, and complex. However, Industry 4.0 is expected to radically change the future of ramp-up management. Since the ramp-up is ill-understood, the goal of this work is not only to quantify early-stage ramp-up performance but also to enable companies to accelerate ramp-up such that they secure their mission toward mass manufacturing as well as their digital transformation. This work contributes to the field of ramp-up manufacturing by (i) introducing a ramp-up performance measurement framework for job shops including seven performance indices suitable for companies in ramp-up (ii) designing and implementing a low-cost and scaleable Real-Time Location System that can capture real-time positions of products on the shop floor. The effectiveness of the proposed framework and Real-Time Location System is assessed by deployment at a photonic semiconductor foundry in ramp-up and testing the performance measurement framework accordingly. Results show that the proposed framework is capable of quantifying how far a production process is removed from ramp-up. On top of that, it is demonstrated that the proposed Real-Time Location System reveals additional information, such as exact production pathways, that an existing WIP tracking system is not capable of capturing during this stage.

Keywords: Ramp-up, job shop, Real-Time-Location-Systems, manufacturing, Industry 4.0

Contents

1 Introduction

Moving a new technology from development to mass manufacturing brings technical, financial, and organizational challenges for companies. Within established production industries, e.g. consumer electronics, automotive, and semiconductor, the investments required for mass manufacturing can go up to multi-million or even multi-billion dollars. The pressure on recovering the initial investment is immense. Especially during the start-up phase of such a transition, the pressure on increasing production volume is enormous. Besides, swift and early start-up of mass manufacturing maximizes the financial profit and return on investment (Terwiesch, Bohn, & Chea, 2001; Weber & Yang, 2014). Some authors even state that an aggressive capacity ramp rate is vital for the commercial success of the enterprise (Haller, Peikert, & Thoma, 2003). The start-up phase of mass manufacturing is also referred to as the 'ramp-up'. Ramp-up is a poorly defined concept within manufacturing (Terwiesch & Bohn, 2001), which is the key motivation behind this work. We define ramp-up as the period between unstable, project-based pilot production and stable, routine-based series production (Figure 1).

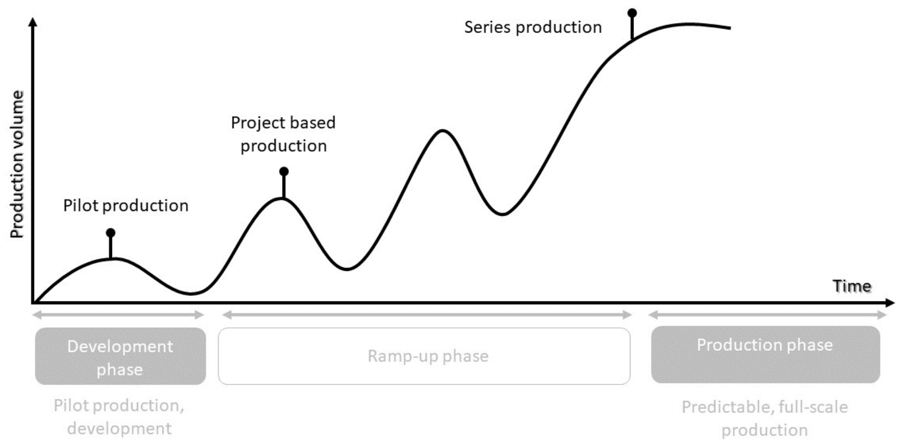


Fig. 1: Position of ramp-up phase in manufacturing

The challenge during ramp-up is that the production processes are ill-understood. Reaching consistency in output is of more significance than a one-off good result (Doltsinis, Ratchev, & Lohse, 2013). In particular, the early-stages of ramp-up contain immature production processes. Although Figure 1 implies a division between the development and ramp-up phases, these phases often happen simultaneously due to product improvement cycles and/or companies with multiple product lines. Not surprisingly, for a manufacturing environment yield, the earnings generated over a specific period of time against the investment, can stay low for multiple years during the attempt to ramp-up production. An example is the semiconductor industry, which already expressed the urgency for acceleration during the ramp-up (Benfer, 1993; R.C. Leachman, 1996).

A production environment with similar machines and workstations for a variety of products is typically considered a job shop (G.Q. Huang, Zhang, & Jiang, 2008). Additionally, job shops typically consist of various (re-entrant) manufacturing jobs assigned to a variety of machines. Examples of job shops are automotive, hard disk, and semiconductor production processes. Automation has always been the driving force behind mass manufacturing in job shops. It results in cost reduction, increased quality, and reduced manufacturing cycle times allowing production companies to stay ahead of the competition (Keith, 1996). Automation is accelerated due to the rise of Internet of the Things (IoT) (Monostori et al., 2016; Uhlemann, Lehmann, & Steinhilper, 2017). Standing on the eve of the fourth industrial revolution, manufacturing obtained a new dimension due to IoT, which enhances the level of automation and enables production companies to create an extra layer of visibility using low-cost IoT sensors. As a result of the increased availability and resolution of production data, a (near) real-time snapshot of the production process is created. Before, manual acquisition of data in production environments took up the majority of the time (Pawellek, 2014). Consequently, a better understanding of the production process should lead to a more predictable and shorter ramp-up time (Ball, Roberts, Natalicchio, & Scorzafave, 2011; Hentz et al., 2013). In specific, indoor positioning and real-time asset tracking solutions increased in popularity piggybacking on the so-called Industry4.0 concept (Klaus Schwab, 2015): increased connectivity and smart automation within industrial environments. Such solutions, which identify the location of objects throughout the manufacturing process (near) real-time using IoT sensors, are referred to as Real-Time-Location Systems (RTLS) (Rácz-Szabó et al., 2020).

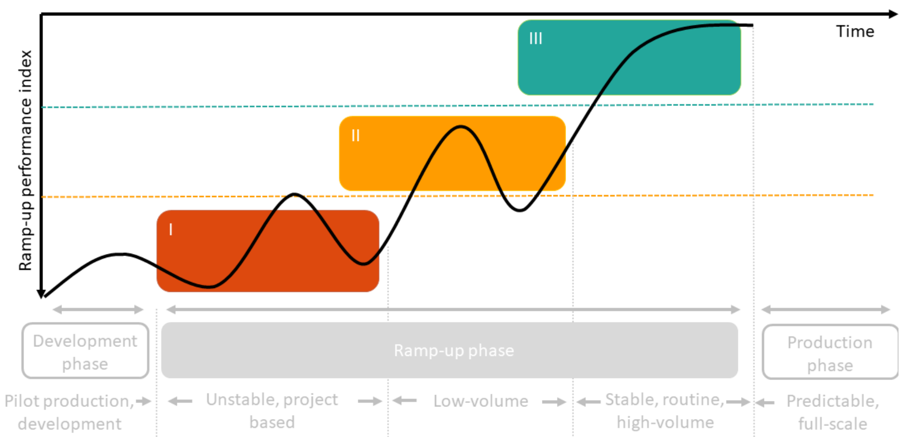


Fig. 2: Ramp-up performance index and ramp-up zones. **I:** start ramp-up **II:** ramping up **III:** ramp-up completed.

A research gap for adequate performance management of (early-staged) ramp-up manufacturing has already been identified by Terwiesch and Bohn (2001). Consequently, our work aims to fill this gap by contributing to production performance management of ramp-up production by leveraging existing IoT applications. Figure 2 presents a schematic representation of the contribution. The ramp-up performance measurement framework differentiates between three different stages in ramp-up, which will be introduced later. Ramp-up performance is quantified using a single ramp-up performance index consisting of the aggregated result of multiple individual indices representing ramp-up characteristics.

More specifically, the contribution of this work is two-fold: first, we present a ramp-up performance measurement framework for job shops leveraging real-time production process data collected by an RTLS. The scope of the proposed ramp-up performance measurement framework considers different ramp-up performance metrics to be evaluated over time. Secondly, a low-cost component RTLS is developed to capture real-time positions of products. However, the main contribution of this work is not designing and implementing an RTLS, but rather leveraging the extra production visibility of the position data generated by an RTLS. To the best of our knowledge, this work is the first to leverage real-time position information coming from an RTLS to quantify ramp-up performance. Hereby the aim is to contribute to the field of ramp-up production of a job shop.

To achieve a contribution to this field, this work aims to address the following research question: *How can real-time location systems contribute to ramp-up performance measurement of job shops?* The underlying hypothesis is that an RTLS reveals the discrepancy between what companies 'think' that is happening in their production process and what is actually happening. In general, we believe better decisions can be made during this chaotic and unpredictable ramp-up phase (Terwiesch et al., 2001)

Beyond RTLS in ramp-up manufacturing, this work aims to unravel the potential of real-time data-generating IoT applications in an early stage of the ramp-up process and demonstrate the power of real-time data in ramp-up manufacturing. Additionally, this work possibly assists production companies in their digital transformation. During this transition, decision-making on the operational level switches from daily time intervals to real-time. Adequate responses on (un)foreseen events become more and more important as the number of jobs keep rising.

This work is organized as follows. In section 2 related work in the field of ramp-up manufacturing, ramp-up production, and IoT in manufacturing are discussed. Moreover, section 3 elaborates on the research methodology containing the RTLS design and proposed ramp-up performance measurement framework. Subsequently, section 5 introduces a case study within the semiconductor industry for which the framework and RTLS were implemented. Lastly, section 6 presents the results of the proposed ramp-up performance measurement framework for the case study followed by the discussion and conclusion.

2 Related work

This section discusses related work starting with studies on ramp-up manufacturing industries and key drivers towards a successful ramp-up. Moreover, a more detailed overview of work considering the ramp-up of job shop environments is presented followed by a narrow review of leveraging real-time data in the ramp-up of complex production environments.

2.1 Ramp-up production

The field of ramp-up production processes is studied extensively since the late 80's, begin 90's, and onward Benfer (1993); Bohn (1995); Bradbee, Gates, and Wilcox Jr. (1989); Flaherty (1990); Leachman (2002). However, the studies on ramp-up production are overshadowed by operational research which focused on time-to-market, which explicitly excludes the ramp-up phase. Due to the shift of high-tech production companies from time-to-market to time-to-volume during the 00s, putting the tail end of the ramp-up in a critical position (Terwiesch et al., 2001). Ever since the first mention of ramp-up production processes in manufacturing it is a poorly defined concept. Some authors define the ramp-up phase as the time interval from the end of the prototyping phase to the full-volume production (Sturm, Dorner, Reddig, & Seidelmann, 2003). Others approach the ramp-up phase as the period between the completion of development and full capacity utilization (Terwiesch & Bohn, 2001). Terwiesch et al. (2001) define the production ramp-up as the period during which a manufacturing process makes the transition from zero to full-scale production at targeted levels of cost and quality. Ball et al. (2011) present a wider view of the ramp-up in an attempt to make it a topic standing on its own. Different definitions of a ramp-up are presented here, but their work also detected agreements among the authors' definition of a ramp-up. In short, an exact definition of a ramp-up in manufacturing is not explicitly stated in the literature. Since this work does not attempt to clarify the ambiguity in definitions of ramp-up phases in manufacturing, it was decided to adopt an existing definition. Considering previous work, from now on the ramp-up phase in this work is defined as the period between unstable, project-based pilot production and stable, routine-based series production (Figure 1).

Automation is key to series production. Several key drivers behind automation have been established over the years (Nof S. Y., 2019). Material-handling is mentioned as the first key driver towards fully automated wafer fabs. A second driver is the reduction of operators, which remain the significant source of particle generation inside cleanrooms. Another important driver behind fab automation is standardization for reducing integration effort and performance risk. This third driver closely relates to the purpose of Semiconductor Equipment and Materials International standards (SEMI) standards [1].

Measuring the performance of ramp-up manufacturing is a challenging task. Mainly because manufacturing-related processes are ill-understood during the

[1] www.semi.org/en/Standards/P_000787

ramp-up phase, resulting in low yield and production volumes (Terwiesch & Bohn, 2001). Yield, the earnings generated over a specific period in time against the investment, can stay low for multiple years during the attempt to scale up production. Multiple studies discuss the phase in which investments were high and volumes stayed low (Benfer, 1993; R.C. Leachman, 1996).

2.2 Ramp-up in job shop environment

Ramp-up production is particularly complicated for job shops. Terwiesch and Bohn (2001) expresses the urgency for learning during the ramp-up phase in a job shop environment. Meaning, although production costs are at their highest and yield at their lowest, it is key to run engineering trials and keep improving the understanding of production processes. Simulation-based approaches to test the effect of dispatch rules or batch sizes on yield are well-known in the field of job shop ramp-up (Sturm et al., 2003)

Aggressive ramp-up rates guarantee company success, but the risk of unbalanced production systems must be mitigated. Haller et al. (2003) designed a methodology for semiconductor companies that accelerated the ramp-up rate as soon as the factory performance allowed it. By introducing a so-called Work-In-Progress (WIP) 'cap' cycle times were kept at their lowest while improving the yield.

Within the automotive industry, it is stressed to investigate the ramp-up phase prior to the time-to-market process (Clark, 1991). An example from the automotive industry in Sweden addresses the role of information during production ramp-up (Fjällström, Säfsten, Harlin, & Stahre, 2009) in the manufacturing industry. It was found that when critical events occurred during ramp-up the source and type of information were deemed useful when handling the event. Formalized networks need to be established to support information exchange and dissemination, but the role of spontaneous communication by informal information exchange may not be underestimated (Fjällström et al., 2009).

Besides, time-to-market is key to ensuring profits, return on investments, and competitiveness. Weber and Yang (2014) address these elements in a theoretical framework for wafer fab managers helping them make strategic decisions during the ramp-up phase. This work describes three types of wafer fabs: leading-edge manufacturers, fast followers, and slow followers. Here, it was concluded that under no circumstances a slow follower could be more profitable than a leading-edge manufacturer. One could argue that the bias for action is real to guarantee a return on investment.

In particular, Doltsinis et al. (2013) started on a systematic framework to formalize the ramp-up phase and prepare data collection instruments to quantify the performance of ramp-up manufacturing. This work is important because it focuses on the very early stages of ramp-up, which are undefined, unstable, and ill-understood. As use case, they identify the most relevant performance metrics to ramp up a robotic arm based on qualitative and quantitative data.

2.3 Ramp-up using real-time data

Leveraging real-time data of machines is used to improve quality. Nowadays, low-cost sensors increase the ability to collect data on almost all facets of a production line. First, IoT solutions within manufacturing in general are discussed after which we zoom in on RTLS.

2.3.1 Internet of Things in Manufacturing

Several paradigms arose regarding IoT applications within manufacturing operations. Digital twins are seen as a digital equivalent of a physical production process, which allows for optimization with a shorter time between data collection and the creation of the digital twin (Uhlemann et al., 2017). Uhlemann et al. (2017) state that deficits limiting the realization of Digital Twins are the manual acquisition of motion data, which limits the potential of simulation and real-time availability of data. Secondly, decentralized data collection and standardization of data acquisition have not been achieved. Finally, this work mentions the high cost of new IT environments that inhibit the vertical infrastructure for Industry 4.0. A by-product of digital twins is a digital shadow, which is an artifact of a digital twin interfacing with a real-time replica of the physical system (Trauer, Schweigert-Recksiek, Engel, Spreitzer, & Zimmermann, 2020). Somewhat related are Cyber-Physical Systems (CPS). CPS are systems of collaborating computational entities, which are intensively connected with processes in the physical world (Ariane Hellinger & Heinrich Seeger, 2011). In other words, these systems are physical and engineered whose processes are monitored and controlled by a computing and communication core (Rajkumar, Lee, Sha, & Stankovic, 2010).

Cyber-Physical Production Systems (CPPS) arose as a specialist branch of CPS focusing on smart manufacturing. CPPS has the potential to lead to the 4th industrial revolution (Industry 4.0), and relies on the latest developments in the field of manufacturing, communication, and computer science (Monostori et al., 2016).

In another attempt to capture the aspects of IoT applications within manufacturing industries, S. Huang, Guo, Zha, Wang, and Fang (2017) introduced the term Internet of Manufacturing Things (IoMT). IoMT is defined as a multi-source real-time manufacturing information-driven optimal management system for shop- floors. IoMT consists of hardware and software aiming to control the production orders from raw materials to finished products

2.3.2 Real-Time Location Systems (RTLS)

Indoor positioning has become more and more popular in recent years. While low-cost sensors found their way to the market, the accuracy, size, and efficiency of sensors kept improving simultaneously. Hence, RTLS automatically piggybacked from the fourth industrial revolution (Kang et al., 2016).

According to ISO standards, RTLS are "wireless systems with the ability to locate the position of an item anywhere in a defined space at a point in

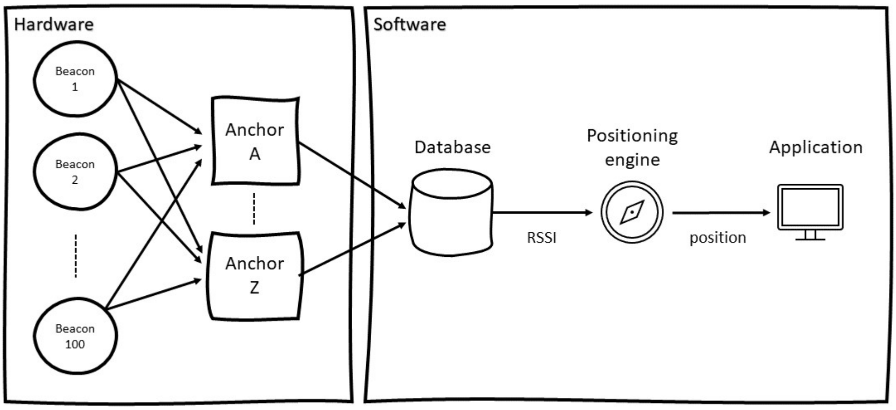


Fig. 3: RTLS infrastructure

time that is, or is close to, real-time. The position is derived by measurements of the physical properties of the radio link." (ISO, 2014).

In general, the RTLS infrastructure consists of four elements. (i) Beacons are placed on objects to be traced. (ii) Fixed anchors which communicate wirelessly with the beacons. (iii) A positioning engine that calculates the positions of beacons via the data it receives from the anchors. Finally, (iv) a user application with an interface between the RTLS back-end and the user. Figure 3 presents a visualization of the RTLS infrastructure.

Applications of RTLS are manifold. Moreover, different communication protocols are established to suit the needs of different indoor localization use cases (Thiede, Sullivan, Damgrave, & Lutters, 2021). Due to this strong use case dependency there is no single technology to support these systems (Rodas, Barral, & Escudero, 2013) and thus no uniform architecture as well.

An RTLS aims to help organizations in optimizing workflow, reveal process times, identify bottlenecks and connect to other IoT systems in the factory (Thiede et al., 2021; Toro, Wang, & Akhtar, 2021). An RTLS has a long history. During their extensive literature study conducted on CPS, Monostori et al. (2016) concluded that Radio-Frequency Identification (RFID) and cloud computing are the two most commonly applied technologies in realizing IoT in manufacturing environments. Other studies used real-time position data of WIP to simulate the benefits of RTLS (Chongwatpol & Sharda, 2013; Nian, Guo, Wei, Jiang, & Yuan, 2014). The results of their work show that RFID-based scheduling rules and WIP control outperform traditional methods concerning cycle time and machine utilization.

Within the semiconductor manufacturing industry, there are some concrete examples. NXP, a Dutch-American semiconductor manufacturer, for example, uses RFID to verify whether the correct lot is loaded on the equipment(NXP, 2014). After the implementation, better control of WIP and real-time movements of lots was realized. Additionally, through this extra layer of visibility, the dispatching process improved, reducing the lead times. Similarly, Infineon

Technologies also installed an RFID-based lot-tracking system, which reduced handling errors and thus the scrap products (Thiesse, Fleisch, & Dierkes, 2006). Similar to our case study Thiesse et al. (2006) stated that wafer fabs typically have a strong customer orientation, which requires flexibility and operator-centered automation to cope with the variability of the process. This work concluded that RTLS can lead to the more strategic use of production flexibility and enhance customer-oriented production. The major difference between our work is twofold. First, Infineon made use of RFID. Second, Infineon decided that besides collecting data, the RTLS should communicate with operators to enhance cleanroom operations.

Taking into account the above-mentioned work, RTLS still faces a lot of challenges: the environment, interference, frequency, desired accuracy, and high investment costs. Besides, selecting the type of RTLS technology strongly depends on the environment and use case (Rodas et al., 2013; Thiede et al., 2021; Toro et al., 2021).

To summarize, the field of ramp-up production is overshadowed by studies on time-to-market, which explicitly eliminate the ramp-up phase. Ergo, ramp-up is ill-understood while it is the key factor of company success. Especially for a job shop like in the automotive and/or semiconductor industry a swift ramp-up is important to guarantee a return on investment. The rise of the fourth industrial revolution and the increasing presence of IoT in manufacturing enabled digital solutions, for example an RTLS, to be smaller, more energy efficient, and cost-effective. With the increasing number of sensors in manufacturing environments, the ability of continuous (near) real-time automated data collection became more realistic. As Schmitt et al. (2018) state, ‘Real-time data is needed during the ramp-up phase to increase the quality and speed of decisions taken by humans’ (Broy et al., 2011; Schmitt et al., 2018).

Table 1: Research gap

	Haller et al. (2003), Fjällström (2009), Keith et al (1996), Terwiesch et al. (2001)	Rácz-Szabó et al. (2020), Thiesse et al. (2006)	Doltsinis et al. (2013)	Smolenaars et al. (2022)
Ramp-up performance	x		x	x
Job shop	x	x		x
Real-time data		x	x	x

To conclude, Table 1 reveals how our work is positioned against the above-mentioned literature. The research gap which we try to fill is the ramp-up performance management of a job shop leveraging real-time production data. By introducing a low-cost scaleable RTLS providing real-time production data in a job shop environment we hope to contribute to a better understanding ramp-up performance. Table 2 provides an overview of the use cases discussed

Table 2: Studied use cases on ramp-up performance measurement

Author	Terwiesch (2001)	Doltsinis (2013)	Clark (1991), Fjällström (2009)	Haller (2003)	Smolenaars (2022)
Case study/In-dustry	Hard disk drive	Gluing robot	Automotive	Electronic Integrated Circuits	Photonic Integrated Circuits

in the above-mentioned literature and our work. The next section will elaborate will elaborate on the proposed ramp-up performance measurement framework.

3 Research Methodology

In order to understand ramp-up performance, two procedures are followed: the development of a ramp-up performance measurement framework and the design of a low-cost RTLS for ramp-up manufacturers. The latter enables a comparison between the location data of products and existing production data. To validate the two procedures a case study at a scale-up photonic semi-conductor foundry was carried out to evaluate the proposed framework and implement the low-cost RTLS. The rest of this section elaborates in detail on each of the elements of the framework.

3.1 Ramp-up performance measurement framework

This section elaborates on the performance measurement framework enabling companies to calculate and design ramp-up performance indicators. A high-level overview of the proposed ramp-up performance measurement framework is presented in Figure 4.

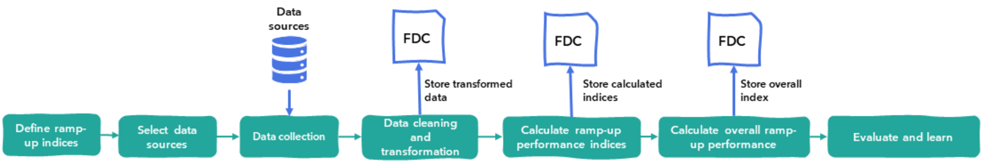


Fig. 4: Ramp-up performance measurement framework

The first step of the framework is identifying suitable ramp-up indices, which reflect on key characteristics of ramp-up production. Secondly, suitable data sources are selected to gather data for the identified ramp-up indices. Thirdly, data from these data sources is collected and subsequently cleaned, transformed, and stored in the factory data cube (FDC). What the exact position of the FDC is in the data collection architecture will be explained in section 3.4. Furthermore, the ramp-up indices are calculated and the results are stored in the FDC as well. Using the results of the previous step the overall ramp-up performance is calculated by aggregating the individual ramp-up indices. Again the result is stored in the FDC. Finally, the overall ramp-up performance, in combination with the individual indices, is evaluated and improved.

3.2 Definition of ramp-up indices

As discussed above, the ramp-up indices are considered key performance indicators of the ramp-up. A ramp-up performance index is defined as an indicator reflecting the performance of a production process in a transition towards high-volume production. Furthermore, it is chosen to adapt the general definition of an index as a concept that should be periodically reviewed and updated (Doltsinis et al., 2013). However, we make a distinction between ramp-up performance indices and registration accuracy indices (Figure 5).

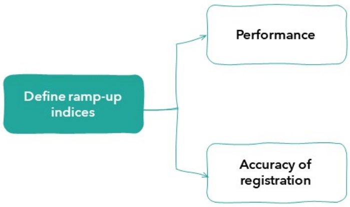


Fig. 5: Definition of ramp-up indices

Performance indices answer the questions *"how well is the production performing?"* On the other hand, ramp-up production processes are considered unpredictable and unstable as mentioned in section 2. Therefore, the second question one should ask during ramp-up performance measurement is *"how accurate is the registration of performance indices?"*. Hence, an accuracy of registration index is defined as an indicator reflecting the degree of deviation between what we register, for example via a Manufacturing Execution System (MES), and what actually happens during the production process.

Regarding the first category (performance indices) existing literature uses established (stable) production processes as use cases assessing performance on cost, quality, flexibility, and productivity (Hon, 2005), also known as the Devils quadrangle (Jansen-Vullers et al., 2007). Nonetheless, performance indicators like cost and flexibility are not necessarily dominant for companies in ramp-up, due to unstable and project-based production. Research and development are dominating during the early phases of ramp-up. Measuring the performance during this transition is often considered troublesome. Similar to Doltsinis et al. (2013), the proposed framework formally captures the ramp-up performance by introducing multi-dimensional indices reflecting important ramp-up characteristics, which will be introduced hereafter. Yet, the proposed ramp-up performance measurement framework differs in terms of scope and granularity compared to the performance framework of Doltsinis et al. (2013).

First of all, the focus of our work is on a job shop including multiple workstations instead of a single workstation. Second, Doltsinis et al. (2013) assume that the ramp-up of a (set of) machine(s) is defined as a sequence of adaptions and adjustments applied to a system, but our work also acknowledges the system's unpredictability and instability resulting over time. For example, (un-)scheduled breakdowns of machines resulting in factory and/or machine down-times.

Table 3: Overview of ramp-up performance and registration accuracy indicators

ID	**performance indicators**	ID	**registration accuracy indicators**
1	production disruptions	5	pathway deviations
2	completed production steps	6	production visibility
3	quality of products	7	production traceability
4	process time		

Given the distinction between performance and accuracy of registration indices, Table 3 introduces the relevant indices for the proposed ramp-up performance measurement framework. The motivation and terminology are associated with each ramp-up index based on generic job shop terminology after which each index is explained in more detail as follows:

1. production disruptions: the number of equipment downtime registered by an MES, according to industry standards (for example SEMI standards within the microelectronics industry (SEMI, 2021)). This index ($f_1(t)$) aims to emphasize the magnitude of disruptions encountered during period t, which is one of the main issues in the ramp-up phases (Doltsinis et al., 2013).
2. completed production steps: the number of completed production activities in a production process during period t. This index ($f_2(t)$), accounts for the completion of registered production steps. The complexity of job shops is a key motivation behind this index, since early-stage ramp-up processes suffer from ill-understood production processes.
3. quality of products: the quality standards and/or desired quality of products produced measured via the number of rework steps performed during period t. Increasing quality while reducing cost is one of the key challenges during ramp-up (Ball et al., 2011). Therefore this index ($f_3(t)$) is included as a ramp-up index.
4. process time: actual time a person or machine spends on a specific production step. This index ($f_4(t, m)$) captures mean process times of production steps at each machine during period t.
5. pathway deviations: discrepancy between the registered pathway of products through the production process versus the actual pathway. This index ($f_5(t)$) quantifies the similarity between when and where production steps are registered and when and where they are actually happening during period t. Deviations in the registered and actual pathway are considered as an indicator contributing to a successful ramp-up process, because early

ramp-up production processes are often ill-understood and insufficiently documented.

6. production visibility: the deviation between the number of registered production steps and the actual number of production steps during period t. This index ($f_6(t, m)$) is somewhat related to the completed production steps index ($f_2(t)$), but rather focuses on the deviation of the registered and actual completed number of steps. Similar to the previous index, the motivation behind production visibility as an accuracy indicator is the fact that insufficient visibility of production steps contributes to a slower ramp-up.

7. production traceability: difference in registered process time per step and actual time spent at the workstation during period t. Similar to ($f_4(t)$) this index looks at time spent at a machine or workstation, but this index ($f_7(t, m)$) aims to quantify the lack of traceability in registering the real process times of production steps performed at each machine. This index is motivated by the fact that capacity planning decisions need to be based on the correct processing times of products and tools. Incorrect information contributes to slowing down the overall ramp-up process.

Each of the above-mentioned ramp-up indices takes t as input, stating the period over which the index is calculated. As such, each index is not continuous but looks over discrete consecutive periods t of equal size. Depending on the scope and granularity of the case study, t can be set to minutes, hours, days, weeks, etc. Next, each of the introduced ramp-up performance and registration accuracy indices will be discussed in detail.

3.2.1 Production disruptions

In contrast to streamlined production processes - in which unexpected disruptions can be predicted accurately - ramp-up production processes suffer from unexpected events, such as down-times, machine breakdowns, etc. Let J be a set of disruptions of manufacturing resulting from non-conformance, e.g. (un)scheduled machine downtimes and/or out-of-stock. Such disruptions negatively impact the continuity of the production process, the cycle times of products, and consequently the ramp-up speed. Capturing the above-mentioned disruptions is done by adopting and modifying the first index of (Doltsinis et al., 2013) presented in Equation (1)

$$f_1(t) = \sum_{j=1}^{J} x_{t,j}\gamma_j \tag{1}$$

where $x_{t,j} \in \mathbb{N}_0$ represents the number of disruptions of type $j \in J$ in period t. Each disruption j is weighted by a factor $\gamma_j \in [0, 1]$ allowing for different impacts associated with disruptions.

3.2.2 Completed production steps

Whereas the performance of production systems is normally assessed in terms of throughput, the rate of production, early-stage ramp-up consists of a mix of R&D and production activities. Consequently, a basal performance indicator used within manufacturing ramp-up is the number of production steps completed per time unit per equipment. A production step is defined as the completion of a process not differentiating between production and R&D since these types of processing are somewhat intertwined during ramp-up. On that account, this second index captures the performance of the production process in terms of completed production steps. Let M be the set of machines, then the total number of completed production steps during period t is

$$f_2(t) = \sum_{m=1}^{M} y_{t,m} \tag{2}$$

where $y_{t,m}$ represents the number of completed production steps during period t at machine m.

3.2.3 Quality of products

Quality of products is very important throughout the ramp-up. More important is consistent quality instead of a one-off good product. Previous work has described the importance of a quality indicator within ramp-up (Doltsinis et al., 2013; Hon, 2005; Terwiesch et al., 2001). However, whereas mature complex job shops use instruments such as yield, the number of good-off products coming out of the production process over the total number of started products (Zhu, Johnsson, Varisco, & Schiraldi, 2018), to approach the quality performance of their production process, yield is not always suitable for early-stage ramp-up production companies. For example, yield is heavily influenced by R&D activities which are symbolic for early-stage ramp-up. To underline, if yield can be used, this must be preferred over an alternative performance measure, but especially early-stage ramp-up normally does not lend itself to this way of quantifying product quality. Alternatively, to avoid focusing on one-off good products the third index looks at the number of rework steps performed during a certain period t. Zhu et al. (2018) already identified rework as a manufacturing performance indicator. Rework is identified as an extra production step required to recover a products state before it can continue the regular production flow. Let W be the set of rework steps that can be performed on products to restore the desired quality. Then the third ramp-up performance index is presented in Equation (3).

$$f_3(t) = \sum_{w=1}^{W} a_{t,w}\epsilon_w \tag{3}$$

where $a_{t,w} \in \mathbb{N}_0$ represents the number of rework steps of type w during period t. Similar to production disruptions each rework step is weighted by a factor $\epsilon_w \in [0, 1]$ allowing for different impacts associated with rework steps.

3.2.4 Process time

Key in manufacturing ramp-up is the introduction of a WIP tracking system e.g. MES. The establishment of an MES enables managers to steer the operation better. Especially in job shop environments collecting actual process and cycle times is a challenging or sometimes impossible task. Continuous changes in the way of working in conjunction with research and development crossing production increase the complexity of collecting accurate timestamps. Even with an MES in place, the resulting discrepancy between actual and theoretical process times may negatively affect the ramp-up. For example, decisions regarding the optimization of planning, capacity, and shifts can only be based on accurate theoretical process times for each production step. Let M be the set of machines and S the set of all production steps. Then $S_{m,t}$ is the set of production steps completed at machine m during period t. For all $m \in M$, the fourth index captures the average process time for a specific workstation during period t

$$f_4(t, m) = \frac{\sum_{s \in S_m} d_{t,s,m}}{y_{t,m}} \tag{4}$$

where $d_{t,s,m}$ refers to the registered duration of process step s completed at machine m during period t. Similar to Equation (2) $y_{t,m}$ denotes the number of production steps performed during period t at machine m.

3.2.5 Pathway deviations

Ideally, the position and historical pathway of a product should be known at all times. The real-time position is of interest for process speed (search time for products), whereas the pathway is of importance for quality purposes. For example, if a machine had a wrong setting one would like to know which batches went through this machine and when to safeguard the quality of the end product. During ramp-up, this level of visibility is often not present. Reality may be different from what is registered because of rework and or R&D activities. Therefore, the fifth ramp-up performance index aims at answering the question: *where have products been compared to where one assumes they have been?* Let r be the pathway that a product completes throughout the production process. If r contains visits to three machines (nodes) m_1, m_2, m_3 then r consists of a set of edges $[e_{m_1,m_2}, e_{m_2,m_3}]$, where e_{m_i,m_j} represents the edge between m_i and m_j where $i, j \in M$ and $i \neq j$. Let R be the set of pathways r visited during period t. To evaluate the difference between where batches have been versus where one thinks they have been, we are interested in

$$f_5(t) = g(R_t, R'_t) \tag{5}$$

where $g(R_t, R'_t)$ is the similarity between R_t, the set of pathways registered by a regular MES and R'_t, the set of pathways actually visited by a product during period t. The similarity is represented in Equation (5) as a function g taking R_t and R'_t as input parameters. Computing the similarity of trajectories is a fundamental operation in movement analytics (Tao et al., 2021). The similarity of pathways can be calculated in different ways. Some common methods for $g(R_t, R_t')$ are presented in Figure 6.

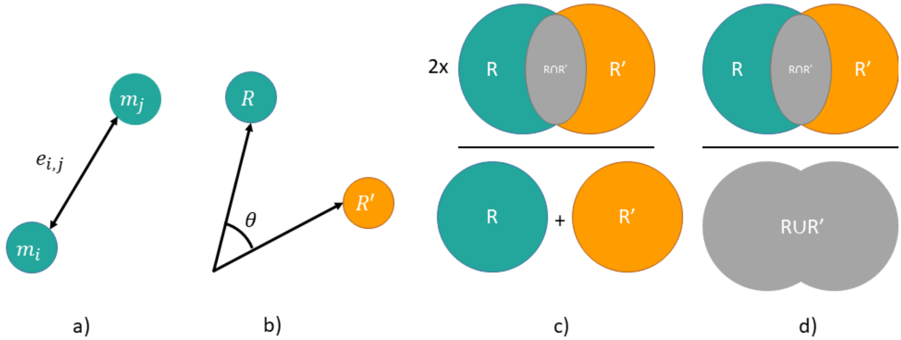


Fig. 6: Some common similarity metrics between sets: **a)** Euclidean distance **b)** cosine similarity **c)** Sørensen-Dice **d)** Jaccard

Equation (5) returns a measure of similarity, a positive value between 0 and 1, where 0 reflects no similarity and 1 implies two sets of identical pathways.

Each similarity metric has its characteristics and depending on the case study one should select a suitable metric. Therefore the chosen similarity metric for our case study is motivated in section 6, but this section briefly highlights the (dis)advantages of commonly used similarity metrics. Almost all similarity metrics are derived from the Euclidean distance similarity, which calculates the shortest distance between two points (Liberti & Lavor, 2017). It will output the distance of a pathway r, but will not quantify the difference in order when comparing a set of pathways between R and R'. Also, Euclidean distance does not scale well with larger data sets (Koutra, Parikh, Ramdas, & Xiang, 2011). In addition, the cosine similarity metric neglects the distance between points but looks at the orientation of pathways. This technique is often used in text mining to compute the similarity of documents (Koutra et al., 2011), but also to compare historical car routes (Akter, Patwary, Akter, & Nahar, 2014). The cosine angle between two pathways r indicates the similarity in orientation. The main advantage of this technique is that it does not take into account the length comparing a set of pathways between R and R', since it is reasonable to assume there are a lot of differences between the real-time and registered pathways. The main disadvantage is the fact that the magnitude (distance) is not taken into account. Thirdly, the Sørensen-Dice coefficient is an intuitive similarity metric indicating the similarity between two sets of pathways R and R' by looking at the percentage of overlap. We define overlap of pathways as common edges (e_{m_i,m_j}) present in both R and R'. Using Figure 6 the Sørensen-Dice similarity can be calculated by two times the intersection of sets of pathways R and R' divided by the sum of R and R'. This similarity metric is often used in sparse data sets (Koutra et al., 2011) and can also be justified as the intersection of two fuzzy sets (Roberts, 1986). Compared to the Euclidean distance similarity, the Sørensen-Dice similarity gives less weight to totally different pathways (outliers), which retains the sensitivity for sparse data sets. Its main disadvantage is the overstatement of sets of pathways with minimal positive overlap. A similar, but slightly altered and commonly used similarity metric is the Jaccard index (Jaccard, 1912), which calculates the size of the intersection divided by the size of the union between sets of pathways R and R'. Figure 6 illustrates the intuition behind the Jaccard similarity, which is to compare the intersection between sets of pathways relative to the size. Jaccard similarity is often used in text mining and e-commerce to identify similar texts and customers respectively. In our case, it is highly related to the Sørensen-Dice similarity, since both weigh each pathway against the size of sets. On the other hand, the main disadvantage of Jaccard similarity is the impact on the size of the union for large data sets.

3.2.6 Production visibility

Apart from the discrepancy in the pathway of products, the number of registered production steps also play a vital role in the maturement of ramp-up. For example, if more steps are happening in real-time than registered one could state the visibility of the production process is lacking behind. Again, let M be the set of machines, then for all $m \in M$ the sixth index captures the accuracy of the number of registered completed production steps

$$f_6(t, m) = y_{t,m} - y'_{t,m} \tag{6}$$

where $y_{t,m}$, similar to Equation (2), denotes the number production steps performed during period t at machine m registered by an MES. Since we are now interested in how accurate the number of registered production steps is, $y'_{t,m}$ refers to the number of actual production activities completed during period t at machine m.

3.2.7 Production traceability

The third and last registration accuracy index, and the seventh and final index in total aims to quantify the accuracy of the amount of allocated time that can be traced back to specific production steps. For example, if an MES registers a process time of 1 hour at a certain workstation, but in reality, it was only there for 30 minutes. Then for the remaining 30 minutes, this process cannot be traced. In line with the motivation behind this index, which states that ramp-up decisions require correct information, the production traceability for all $m \in M$ is characterized as

$$f_7(t, m) = \sum_{s \in S_{m,t}} (d_{t,s,m} - d'_{t,s,m}) \tag{7}$$

where, again, M is the set of machines and $S_{m,t}$ the set of production steps completed at machine m during period t. Similar to $f_4(t, m)$, $d_{t,s,m}$ refers to the registered duration of process step s completed at machine m during period t and $d'_{t,s,m}$ refers to the actual time spent on process step s at machine m during period t.

3.3 Data sources

Given the above-mentioned identified ramp-up indicators, divided over performance and registration accuracy indicators, this section is dedicated to selecting suitable data sources to gather the information required to calculate the indices.

The most common baseline of every production system that aims to ramp up towards high-volume production is an MES. This is the linkage between manufacturing and office planning (Qiu & Zhou, 2004). Traditionally, ramp-up stages are characterized as unstable, unpredictable, inflexible, and complex. However, Industry4.0 is expected to radically change the future of ramp-up management (Schmitt et al., 2018). Besides the MES, an RTLS is selected as the most suitable data source to collect real-time location data from products during the production process. A detailed elaboration on the RTLS design, hardware, and software will be discussed in section 4. Important to note that in practice an MES system can be replaced by other information systems guiding the production, e.g. Enterprise Resource Planning systems if an MES system is not present.

Conversely, both systems have their limitations. Since MES and RTLS are selected as data sources the number of candidate ramp-up performance indices are limited. An overview of indices covered by MES and RTLS is presented in Table 4. Additionally, to indicate which performance indicator is primarily measured by a data source 'X' is used as a notation whereas 'x' denotes when this data source's primary goal is not to capture this indicator.

Table 4: Coverage of ramp-up performance indicators by selected data sources

ID	Indicator	type	MES	RTLS
1	production disruptions	performance	X	
2	completed production steps	performance	X	X
3	quality of products	performance		
4	process time	performance	X	X
5	pathway deviations	registration accuracy	x	X
6	production visibility	registration accuracy	x	X
7	production traceability	registration accuracy	x	X

As demonstrated in earlier work RTLS in job shops can capture objects concerning location and time (Arkan & Van Landeghem, 2013; Chongwatpol & Sharda, 2013; Nian et al., 2014; Thiesse et al., 2006). Moreover, an RTLS is not able to capture immediate disruptions of the production process ($f_1(t)$) as well as the quality of products ($f_3(t)$). Similarly, we assume an MES is not able to capture the quality of products. This might be the case in a more mature stage of production where product quality is fed to the MES, but for early-stage ramp-up, this is often not in place yet.

3.4 Data collection and architecture

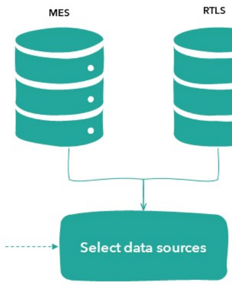
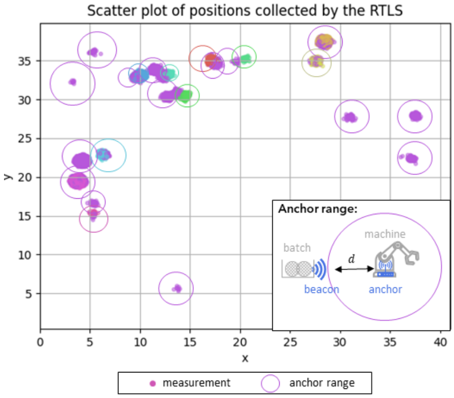


Fig. 7: Selected data sources

This section describes the data collection and ramp-up performance measurement architecture according to the data sources provided in section 3.3 and visualized in Figure 7. Before this architecture is described, it is important to have an understanding of the difference between RTLS data and MES data. Figure 8 illustrates the format of RTLS data when processed by the positioning engine. Table 6 is an example of the most relevant columns collected during a production step by the MES.



Columns	Value
X	14.93
Y	31.05
Timestamp	2022-07-27 10:37:31.68
Zone	Rack 4
Beacon ID	B59
Anchor ID	A34

Fig. 8 & Table 5: Scatter plot of collected object x,y positions (left) and example of data entry row (right)

MES data entries (Table 6) relate to a specific process step and related equipment. However, the major disadvantage is the dependency on operator

Table 6: Example of MES data

WaferID	BatchID	Step	Start	Duration	Equipment	Flow	User
125235	1201	Wet-etch	2022-10-04 10:31:05.27	856	Wet-bench 1	PFA	John Smith

activities. Data only changes if an operator executes an activity in the MES on a PC or tablet. Data generated by the RTLS (Figure 8) on the other hand is indirectly related to a production activity, but rather a physical location. Based on its physical location one can relate the position to a self-defined zone in which certain production steps are performed.

Figure 9 provides the ramp-up performance measurement architecture including the proposed RTLS embedded in an existing factory information system infrastructure.

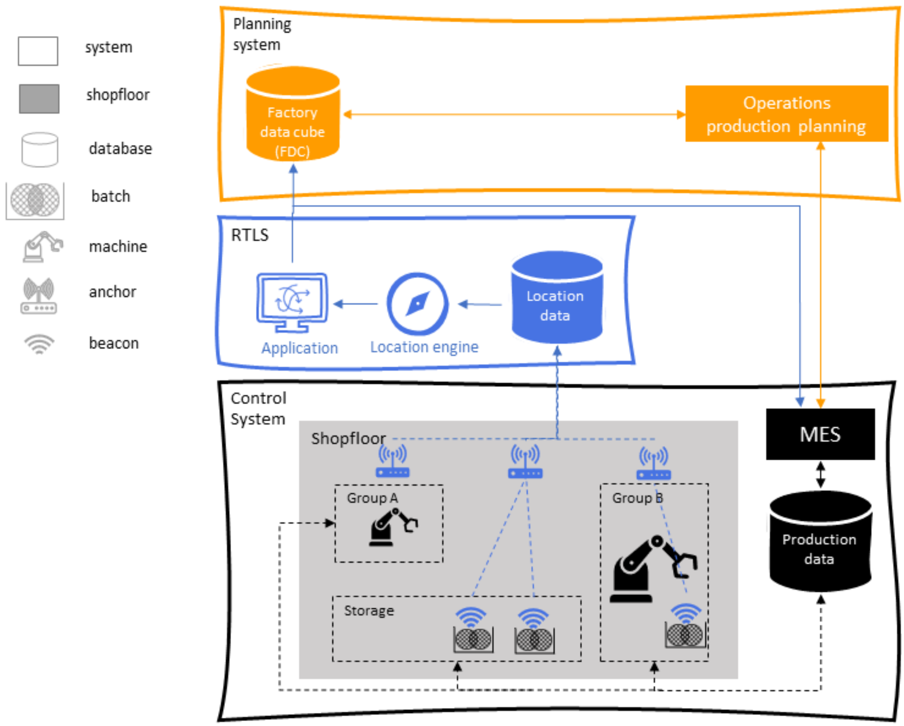


Fig. 9: Data and information system architecture

The ramp-up performance measurement architecture consists of three different layers: a planning system, RTLS, and control systems. Some also refer to the division of planning and control systems as front-end (business related) and back-end (shop-floor-related) systems (Qiu & Zhou, 2004). This division is the most generic enterprise information system architecture and therefore suitable for companies in ramp-up, which often do not have advanced information systems in place yet. The three layers are now described in more detail.

The planning layer contains business-oriented information systems such as sales management, Enterprise Resource Planning (ERP), and production planning. Such systems enable companies to increase their revenues by channeling services and sales more efficiently. At the back-end, the control layer consists of systems that control machines, production execution, and production logistics. For example, an MES system or quality management system. Control systems typically focus on reducing manufacturing-related costs and efficient back-end applications (Lars Mönch, John W. Fowler, & Scott J. Mason, 2013). In general, the RTLS is a layer positioned alongside the shop floor and business-related systems (Thiede et al., 2021). The RTLS hardware and software is capable of capturing (near) real-time positions of batches on the production floor. Beacons were attached to batches and anchors were placed at fixed locations (workstations, machines, storage) on the shop floor and communicated locations to a central database. The location data was then fed to the location engine which interpreted the raw measurement to the real-time location of batches. Subsequently, an application added business logic to real-time locations such as production zones and constraints. Afterward, the application distributes the location data including context and business logic to both planning and control systems.

3.5 Data pre-processing

Both MES and RTLS data had to be pre-processed before it was used to calculate the ramp-up performance. MES data was reduced to only those entries related to workstations, equipment, or other locations, which were also traceable by the RTLS. Besides, entries like the one presented in Table 6 with missing information were dropped. Regarding the RTLS data, extensive information on signal processing is explained in Appendix 8, but the pre-processing steps after the location engine (Figure 9) are as follows. As discussed earlier in this section, the software already accounts for faulty positions by introducing a threshold of a certain number of observations within 120 seconds before assigning a beacon to a certain anchor. This eliminates most of the incorrect positions, but another challenge when handling RTLS data is two locations close to each other. This results in position 'flipping': objects will be assigned to locations A and B consecutively for short periods. For example, in 60 seconds object X has been 10 times at location A for a duration of 3 seconds and 10 times at location B for a duration of 3 seconds. Position 'flipping' has tried to be overcome during the calibration of the hardware. Nonetheless, it cannot be prevented completely. Ergo, it was decided to remove all entries in the RTLS data of objects present at certain locations with a duration of less than 5 seconds.

In summary, the ramp-up performance measurement architecture described in Figure 9 enables companies in (early-stage) ramp-up to collect and compare production-related information (MES) and product location information (RTLS).

3.6 Calculate ramp-up indices

Since each index contains different units and the goal is to combine them into an overall ramp-up performance index an extra step is required after the individual calculation of performance and registration accuracy indices. This step consists of two parts and is conceptualized in Figure 10.

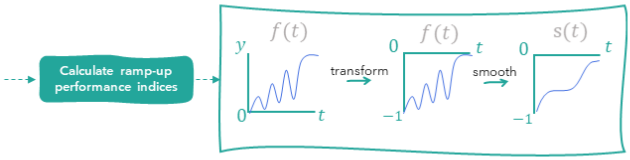


Fig. 10: Calculation of individual ramp-up indices

Firstly, the result of each index is transformed such that its minimum value is equal to -1 and the maximum value is 0. The approach here is to set the completion of the ramp-up equal to 0, and the start of the ramp-up to -1, such that each index indicates how far the index is from reaching its target. Secondly, fine-scaled structures (noise) in the indices are reduced by applying a smoothing technique over the index. It is not an attempt to fit a curve, but solely to focus on the underlying pattern. The consequence of this second part is that each function $f(t)$, which has been transformed between -1 and 0, is smoothed by smoothing function $s(t)$. For sake of simplicity, this works looks into two widely accepted smoothing techniques to reduce fine-scaled structures in the data: simple moving average (SMA) and simple exponential smoothing (SES). section 6 elaborates in detail on which smoothing technique is applied for which index, but below the simple moving average and simple exponential smoothing techniques are briefly explained.

SMA, also known as the 'rolling' average, looks into the mean value of the last k time periods. The value during period t is therefore the mean value of the result between $[t-k, t]$. One remaining question is setting the right value for k. In other words, how many historical time periods $(t-k)$ would one like to take into account when determining the ramp-up performance during period t? It is difficult to define k beforehand without looking at the raw result first. Therefore, k should be determined after inspecting the raw data. As guidelines for setting the value of k for each index individually, one can hold on to the following principles: (i) If zig-zag patterns within the graph are still visible the value of k is too low. (ii) If the peaks are 'washed' away, the value of k is too high and information about a potential underlying pattern is lost. (iii) If the peaks remain visible and the zig-zag pattern has been smoothed the value of k is a suitable candidate. For example, the most right-hand graph ($s(t)$) in Figure 10.

The other technique that is used is single exponential smoothing (SES). This technique has been proposed by Brown R.G. (1959); Holt (1957); Winters (1960) and is often used in forecasting. SES knows a single smoothing parameter $\alpha \in [0, 1]$, which determines how much the result during period t is influenced by previous results. A large value for α indicates shifting importance to only the most recent observations, whereas a low value for α indicates shifting the importance towards historical observations. One difference compared to SMA is that SES uses all historical observations, whereas SMA only uses historical observations of the last k periods.

3.7 Calculate overall ramp-up performance

The combined impact of the aforementioned ramp-up indices completes the proposed ramp-up performance measurement framework. section 3.2 defined 7 ramp-up indicators. Consequently, the overall ramp-up index is the aggregated result of Equations (1), (2), (3), (4), (5), (6), and (7). Mathematically, the overall ramp-up index can be formalized as

$$f_{overall}(t) = s_1(t)\alpha_1 + s_2(t)\alpha_2 + s_4(t)\alpha_4 + s_5(t)\alpha + s_7(t)\alpha_7 \tag{8}$$

where for each ramp-up index, the result is transformed and subsequently smoothed taking into account $t-k$ periods for SMA or α in the case of SES to reduce fine-scaled structures as described in the previous section. Additionally, considering the individual contribution and process-dependent relevance of the multi-dimensional overall ramp-up index, a weight α for each ramp-up index enables the user to account for this effect. Each individual ramp-up index can be read as penalty function. For each index, the following applies: the more negative the more unpredictable, unstable, and ill-understood the process is. The closer it gets to 0 the more predictable your process is and the better the ramp-up process is going. This behavior is transferable to the overall ramp-up index in Equation (8). The lies in the interval [-7,0] where -7 indicates the start of the ramp-up and 0 the final stage of ramp-up completion. Figure 11 zooms in on the conceptual function of the overall ramp-up index across multi-dimensions for a simplified version containing 7 ramp-up indicators. Hence the minimum value is $-7 : \alpha_i = 1$

To give the overall ramp-up index more context, different zones within the index score were created: ramp-up completed, ramping-up, and start ramp-up. We believe the different stages within ramp-up should be investigated further, but these three stages can be seen as basic stepping stones throughout a ramp-up. Table 7 aims to describe the characteristics of these three stages based on the limited work available on ramp-up management (Schmitt et al., 2018; Sturm et al., 2003; Terwiesch & Bohn, 2001). Nevertheless, we want to underline this is just an indication based on the available literature on early ramp-up ramp-up. To the best of our knowledge, there is no work on different stages within the 'tail end of ramp-up' (Terwiesch et al., 2001). To

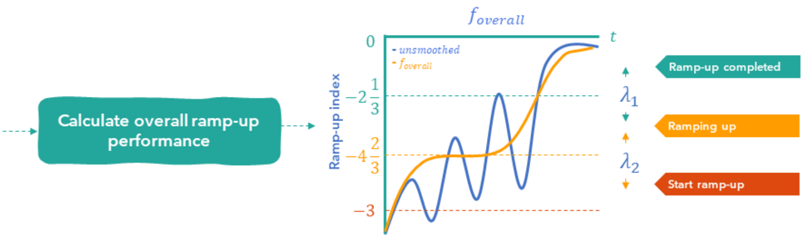


Fig. 11: Calculate overall ramp-up performance

Table 7: Characteristics of ramp-up stages

Stage	**Characteristics**
Near ramp-up completion	stable production, high volume, consistent output, mature, utilizing capacity
Ramping up	project based production, medium volume, slow set-ups, inconsistent output, maturing, underutilized capacity
Start ramp-up	pilots based production, machine breakdowns, low-volume, unstable output, immature, creating capacity

prevent a one-sided subjective interpretation of different phases in ramp-up, the proposed overall ramp-up index contains two model parameters λ_1 and λ_2, which specify the start of the ramp-up completion zone and end of the start ramp-up zone respectively. By introducing these parameters this work aims to trigger companies to define at least three basic stages within the total ramp-up phase until future work provides more clarity. For Figure 11 λ_1 and λ_2 are chosen such that each zone is equally covered over the complete length of the index [-7,0]. In practice, λ_1 and λ_2 should be thoroughly designed by operations management to align with the long-term production strategy.

3.8 Evaluate and learn

The final step of the proposed ramp-up performance measurement framework evaluates the individual ramp-up indices and the projected overall ramp-up index. This step does not contain quantitative methods but connects existing ramp-up approaches from related work and practical experience gained throughout this research. Evaluation of the results should eventually lead to lessons learned. According to Doltsinis et al. (2013), the nature of an index is that it should be periodically reviewed as is the intention of the proposed framework in our work. Only by periodically reviewing the ramp-up strategy based on the proposed indices, the ramp-up can be improved. To conclude the the ramp-up performance framework, evaluating the ramp-up indices regularly is the final step toward ramp-up improvement.

4 Low cost RTLS

This section explains on high-level the RTLS design. A more detailed description of the design and implementation choices can be found in Appendix 8. The focus of this work is not to design an RTLS system that improves existing real-time tracking sensor-based solutions, but rather to investigate the potential of a low-cost solution for manufacturers during ramp-up. Production companies in ramp-up often do not have the resources for a complete real-time tracking solution. On top of that, a flexible and scaleable RTLS is desired during the ramp-up because of continuous changes to increase production volume. To achieve this it was decided to build our own RTLS to reduce the cost and maintain flexibility in fast-changing ramp-up environments.

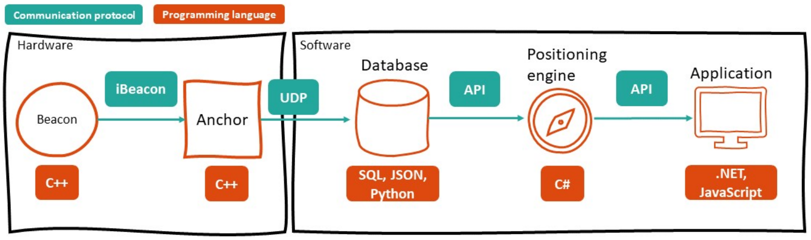
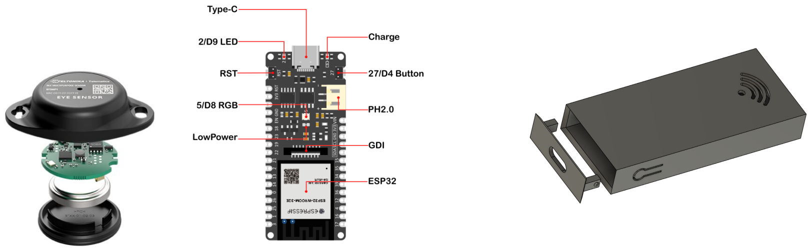


Fig. 12: Detailed RTLS architecture

Although an RTLS does not have a uniform architecture (Rodas et al., 2013) we stick to the 'most generic form' of systems available consisting of: anchors, beacons, a database, a positioning engine, and an application as presented in Figure 3. The protocols for communication between hardware and software and software tools and languages used to build the RTLS are presented in more detail in Figure 12.

Hardware: consists of Commercial Of-The-Shelf (COTS) components. Bluetooth Low Energy (BLE) is chosen as wireless technology, which satisfies the requirements of having an accuracy of $< 1m$. Figure 2a) presents a battery-powered BLE beacon. Figure 2b) presents the anchor which consists of an ESP32-E controller board. Figure 2c) presents the design of the 3D printed anchor casing to protect the anchor against dust.

Bluetooth beacons continuously send out a signal over the iBeacon protocol. Each beacon is attached to a product on the shop floor. Anchors, which are powered over USB-C, are placed at positions of interest. For example, a machine, workstation, desk, storage rack, etc. Each anchor 'listens' to these signals and writes the Received Signal Strength Index (RSSI) values to a database every 5 sec. This is done via the User Diagram Protocol (UDP). Both beacons and anchors are configured by a `C++` script. The database consists of `JSON` files which can be accessed directly using `SQL`. RSSI values represent the amount of power present in a radio signal (measured in dBm), which can be translated



(a) Tag **(b)** Anchor **(c)** 3D printed anchor housing

Fig. 13: a) Teltonika Bluetooth Low Energy beacon controlled by an ST Microelectronics BlueNRG-2 microcontroller. Range up to 80m and weight of 18 gr. Dimensions 56.6mm x 38mm x 13mm[a]. Casing according to IP67 standard. **b)** FireBeetle 2 ESP32-E. Based on a ESP-WROOM-32E main controller board powered by USB-C. 2.4GHz Wifi and BLE module[b]. **c)** 3D printed housing for the anchor.

[a] https://teltonika-gps.com/eye/, accessed on May 23 2022
[b] https://www.dfrobot.com/, accessed on May 23 2022

to a distance measurement (Friis, 1946). The details of this translation can be found in Appendix 8.

Software: consists of the database, the positioning engine, and the application. The positioning engine is connected to the database via an Application Programming Interface (`API`). The RSSI values are then converted to an x,y, and z coordinate. For testing we created a `C#` script to execute this conversion and `Python` was used primarily for data analysis using data coming directly out of the database. To speed up the actual deployment it was decided to replace these tools by software of an external vendor. For this purpose, we partnered with Indutrax GmbH[2], who provided an application that was suitable for our case study. Inside the positioning engine, a presence-detection algorithm was chosen to be suitable of capturing the presence of beacons near anchors. Presence is detected by the number of observations within the range of a specific anchor. For example, if 5 observations within 120 seconds of a single beacon under a certain threshold are measured, the beacon is considered as present at that specific anchor. In reality, the exact number of observations might vary slightly per anchor due to calibration after placement which is explained in more detail in Appendix 8. Lastly, the positions are fed into an application to process movements and enable large-scale data collection. For testing, the application consisted of a simple `.NET` application using `JavaScript`. For deployment, this was also replaced by the Indutrax application. In addition. the application aided in a real-time visual displaying the real-time lots of objects carrying a beacon.

[2]https://www.indutrax.net/

5 Case Study: ‘Lab to Fab‘

In this section, the case study is described for which the proposed RTLS and ramp-up performance measurement framework is implemented in practice. Firstly, background information on the semiconductor industry is provided after which the company is introduced. Thirdly, the implementation of the proposed RTLS at this company is described.

5.1 Background

Integrated Circuits (IC chips). Semiconductors are microelectronic chips that rely on the electronic properties of the material. IC chips are used in almost all everyday electronic devices. The semiconductor industry is one of the few global industries that are in growth modus to smartness (Khakifirooz, Fathi, & Wu, 2019), due to a worldwide continuous demand[3]. Rising numbers of IoT devices and the onward digitization of our world are causing a mismatch between the supply and demand of ICs. The semiconductor industry is not able to adhere to the high volumes requested by their customers. From car manufacturers to telecommunication providers, all low- and high-tech manufacturers are in a battle for ICs (Smith, 2021). ICs are typically manufactured in foundries. Taiwan Semiconductor Manufacturing Company (TSMC) for example is the largest manufacturer of ICs (World Semiconductor Trade Statistics (WSTS), 2022).

Photonics. A special type of IC chip is on its way to change the world of integrated circuits: Photonic Integrated Circuits (PICs). Opposed to regular IC chips, PICs use light and its corresponding properties to carry information, which leads to faster data processing performance and energy efficiency. In more detail, an order of magnitude increase in speed can be achieved by the manipulation of light on a single chip. The expectation is that PICs will lead to a technological revolution similar to the one when regular ICs were introduced in the 1980s. With this opportune prospect and promising results, the European Commission decided to classify photonics as one of the six Key Enabling Technologies (KET) (Müller & Potters, 2019).

Industries using PICs vary from aviation to healthcare and from telecommunication to agriculture. To give an example, data centers are infamous for energy hunger such that energy efficiency is expected to become one of the key purchasing arguments (Poess & Nambiar, 2008). Studies have shown that the use of PICs can reduce power consumption by a factor of approximately 2.2 (Glick et al., 2020). Furthermore, PICs also play an increasingly important role in aircraft, 5G applications, air quality monitoring, autonomous driving, and ultra-secure cryptography.

[3]USD 555.9 billion in 2021 compared to USD 440.4 billion in 2020. A 26.2% increase (World Semiconductor Trade Statistics (WSTS), 2022)

5.2 Company: SMART Photonics

SMART Photonics is a pure-play foundry of Photonic Integrated Circuits (PICs) currently in transition from 'Lab to Fab'. SMART Photonics is in the race of becoming the first foundry of PICs that successfully completes the ramp-up phase. As mentioned in earlier research the success of a company within the semiconductor industry depends heavily on a swift ramp-up to guarantee the return on enormous investments, which are required to scale up production (Terwiesch & Bohn, 2001).

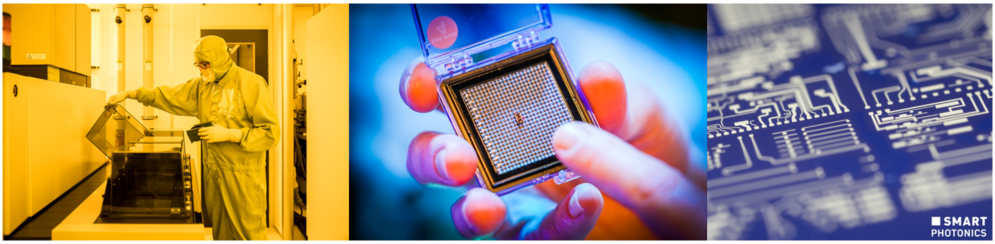


Fig. 14: Impression of SMART Photonics: the process, product, and technology.

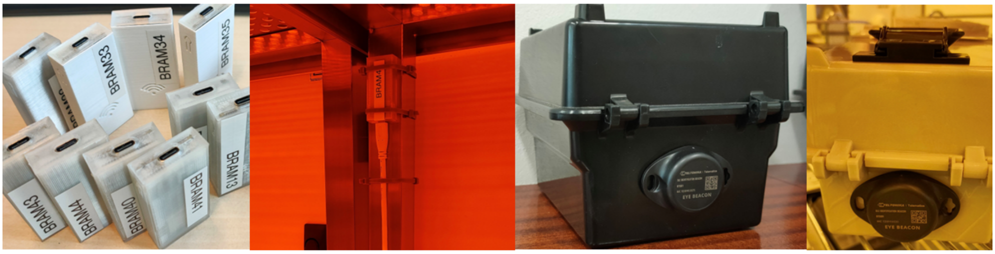
SMART Photonics, a spin-off from Eindhoven University of Technology, now finds its headquarters at the High-Tech Campus in Eindhoven, The Netherlands. SMART Photonics is a foundry offering production services for mainly Indium Phosphide-based photonic integrated components. SMART Photonics offers the complete production process from epitaxial growth and re-growth, processing, polishing, and dicing of wafers into PICs. As an independent pure-play foundry, they support customers from the proof of concept phase up to and including full production. As a foundry, SMART also offers single or combined process steps to complete or be a back-up for the production processes of customers.

From Lab to Fab. The production and manufacturing of (P)ICs are one of the most complex manufacturing processes. At SMART chips are produced on 3- and 4-inch wafers in between 50 and 500 different production steps. The transition from 'Lab to Fab' comes hand in hand with automation, which is mentioned as a key driver behind ramp-up manufacturing. Automation in the company's manufacturing processes is introduced step-by-step according to the internationally-used industrial standard ANSI/ISA-95 for production automation (ANSI/ISA, 2000).

SMART Photonics introduced a manufacturing execution system (MES) in the company as part of the ISA-95 standard (level 3). Besides WIP tracking the implemented system eliminated the majority of the paper flow, guides the production process, and collects manufacturing data. It is the connecting layer between the business (planning) and the production floor (control). The resolution of MES lies between daily reporting and discrete events (hourly/per minute).

5.3 RTLS implementation

In total 20 anchors were placed in the cleanrooms of SMART Photonics and 100 wafer boxes received a beacon attached to the lower back-side of the 3-inch wafer box using 3M double-sided waterproof tape. Figure 15 presents some pictures of the implementation of the anchors and beacons. Important to note is that a single wafer box can carry up to 25 3-inch wafers. Wafer transportation boxes as presented in Figure 15 do not leave the clean room.



a) b) c) d)

Fig. 15: RTLS hardware implementation. **a)** some of the anchors after being programmed and tested outside the cleanroom **b)** single anchor being attached at a workstation **c)** beacon attached to a 4-inch wafer box for testing outside the cleanroom **d)** beacon attached to a 3-inch wafer box inside the cleanroom

The facilities of the case study are densely populated by (metallic) semiconductor equipment and continuously changing due to expanding processes. A selection of 20 workstations was equipped with anchors. Figure 16 presents a conceptual layout of the RTLS implementation.

To process the raw RSSI values and transform them into positions we used the interface provided by Indutrax GmbH to retrieve the positions of wafer boxes in real time. Their application enabled real-time wafer box searching and out-of-the-box analysis instruments. Figure 17 contains a screenshot of the application. Nevertheless, since no tools existed yet to calculate the ramp-up performance we exported the RTLS data from the factory data cube (FDC) (see Figure 9) and analyzed the data using Python (version 3.9).

In total over 305.000 events were registered by the MES between June 2021 and November 2022 was analyzed. The RTLS systems took 6 months to design and develop and were implemented in August 2022. Between August 2022 and November 2022 in total 166.000 data points were collected by the RTLS. However, since not all workstations are covered by the RTLS, the MES data is reduced to events related to workstations that are monitored by the RTLS as well. Therefore, after data inspection and pre-processing MES data related to 23.155 events and 38.256 data points collected by the RTLS are considered as input for the ramp-up performance measurement framework.

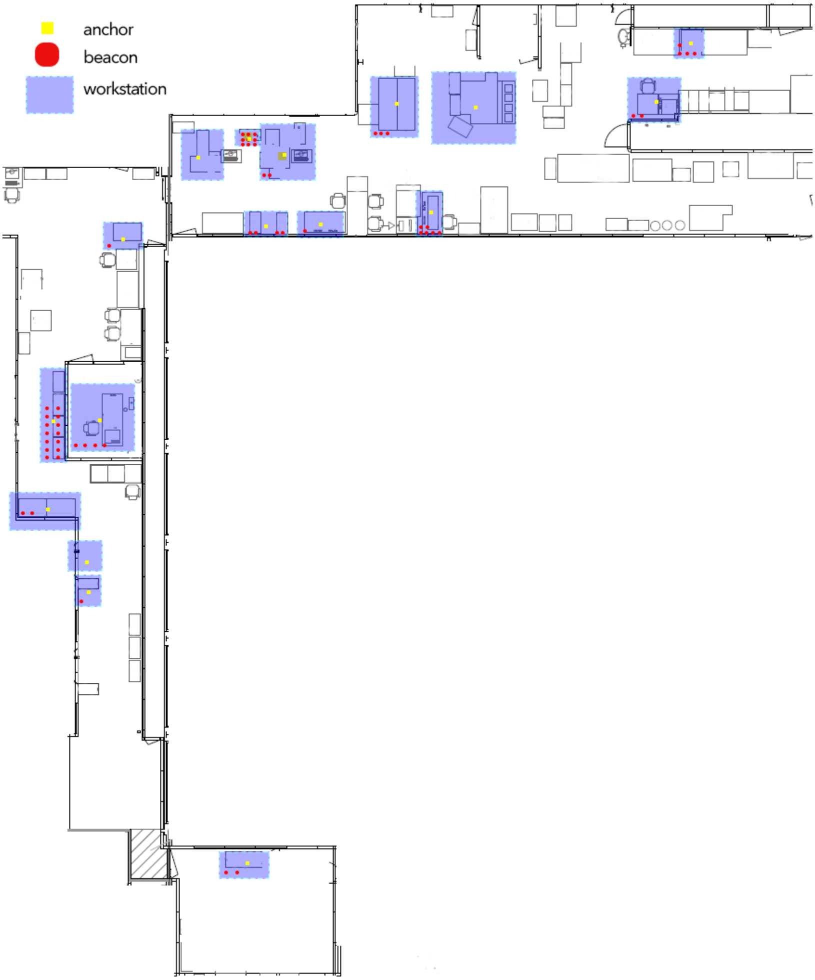


Fig. 16: RTLS implementation

6 Results

This section will discuss the results of the ramp-up performance measurement framework introduced in section 3. Due to confidentiality reasons, the results are anonymized, such that sensitive information regarding the companies production performance can not be tracked. This means that also names of machines and processes are masked or given a pseudonym.

All results are collected via the case study described in section 5. The structure of this section follows the order of each ramp-up index explaining the results one by one and ending with the overall ramp-up index. For our specific case study, it was chosen to set the time period $t = 1$. Meaning, the granularity of the results is calculated over consecutive periods each having a length of

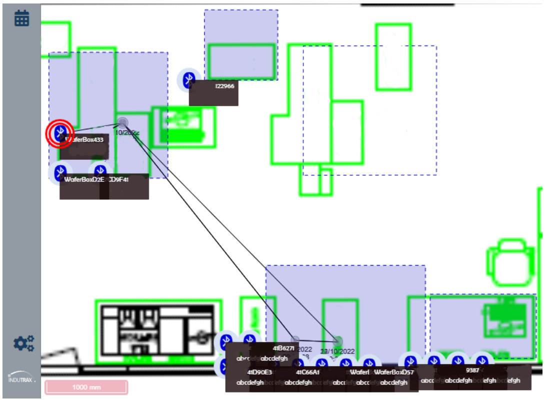


Fig. 17: Indutrax application screenshot

1 day. Apart from the quantitative results, a qualitative exemplification of observations is presented for each index. These examples are reconstructed in consultation with shift leads, engineers, and operators or by observations in the cleanroom. As explained before, a limitation of this work is the fact that the quality performance index ($f_3(t)$) cannot be measured using the chosen data sources. Hence, no results for $f_3(t)$ are collected.

6.1 Production disruptions

First, $f_1(t)$ is calculated using Equation (1) resembling the number of production disruptions. This index can only be calculated with MES data using Table 4. Additionally, the additional weighing factor γ_j was set equal to 1 $\forall j$. For this case study, disruptions of the production consisted of two types of events: a scheduled or unscheduled down event for a machine. Both event types are registered according to the semiconductor industry-wide standards for the specification for definition and measurement of equipment productivity (SEMI, 2021). These standards state that unscheduled down events contain events such as repair, maintenance delay, out-of-specification, etc., whereas scheduled down events contain events such as preventive maintenance, setup, change of consumable materials, etc. Figure 18 presents the result of the number of disruptions over time. Besides the actual values, it appeared that a simple moving average technique taking into account $k = 35$ periods reveals the undulating series of disruptions over time.

The disproportional peak around the start of November 2022 is due to a two-week planned down-time of workstations to make the transition from 3- to 4-inch wafers. This observation underlines the immature and unstable characteristics of early ramp-up. Nevertheless, such activities are necessary to move forward during ramp-up and can therefore not be considered outliers. However, this observation also affects the indexation of the other disruptions. In addition, to turn this result into a workable ramp-up index one extra step is required, which is described in 3.6. The result is first scaled to a range of

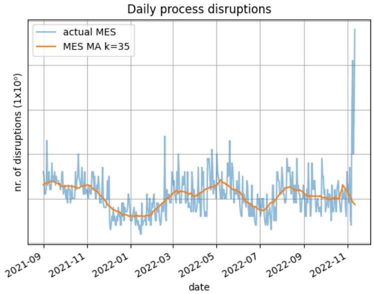


Fig. 18: $f_1(t)$ Production disruptions

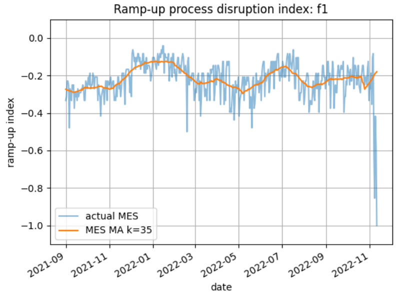


Fig. 19: $s_1(t)$: Ramp-up production disruption index

[0,1] followed by a transformation such that -1 refers to the maximum number of disruptions and 0 to a situation with 0 disruptions. The outcome of this transformation is presented in Figure 19.

To illustrate typical causes of disruptions during ramp-up. Table 8 provides more insight into the origin of disruptions based on qualitative information.

Table 8: Exemplification of scenarios contributing to production disruptions based on qualitative data

Event	Description
Unscheduled-down	Machine stop due to a process out of specification/control limits
Scheduled-down	Machine conversion (e.g. to different wafer size for R&D purposes)
Unscheduled-down	Waiting for machine vendor (e.g. missing spare parts)

6.2 Completed production steps

The second ramp-up performance index $f_2(t)$ tracks the number of completed production steps. According to Table 4, both MES and RTLS are capable of tracking the completed production steps over time. Data collected via the MES provides insights into how many production steps are registered. Six months of MES data was analyzed against 3 months of RTLS data. Figure 20 presents the registered steps via MES and Figure 22 presents the registered steps with the RTLS. Apart from the actual results, it was decided to apply SES with $\alpha = 0.2$ as an additional smoothing technique. Finally, the number of completed steps is transformed to a range of [-1,0] to indicate how far the index is removed from the ramp-up completion. This transformation is achieved by normalizing the number of completed steps against a maximum capacity of steps. This maximum value was established after a discussion with production leads. Consequently, Figure 21 and 23 contain the transformed result indicating the index $s_2(t)$ for both MES and RTLS respectively.

The following observations can be derived from the results. First, the number of moves registered by the MES system seems consistent over time. In certain moments there was no production at all, but no periods with subsequent low completed production steps. RTLS-registered production steps contain more variation. Days with a number of steps close to their maximum capacity are succeeded by days without any registered production step. For sake of clarity, these spikes in the data are not the result of position ‘flipping’ nor incorrect measurements, since these have been filtered out as mentioned in section 3.5. Therefore, these spikes imply that products have been moved to several workstations more often than registered by the MES. It can not be concluded based on this data if these are ‘unauthorized’ production steps, simply because the current MES integration allows for production steps to be performed outside MES. Nonetheless, after discussions with engineers, the most likely explanation for these excessive mismatches is R&D activities not yet implemented in the MES. Overall, the performance index for completed production steps presented in Figures 21 and 23 for MES and RTLS respectively, indicate a process far from ramp-up completion. The explanation for this effect is logical. As mentioned, the result is normalized against the maximum capacity of the number of steps that can be completed per day. During the deployment, the capacity was underutilized resulting in fewer completed production steps per period.

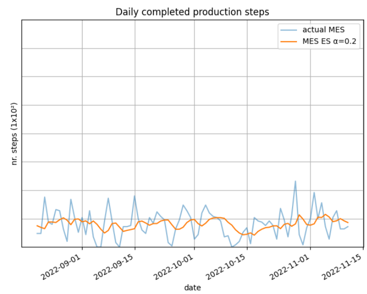


Fig. 20: $f_2(t)$ Completed production steps registered by MES

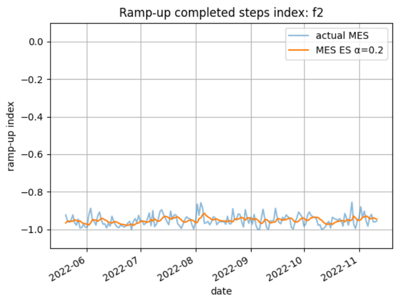


Fig. 21: $s_2(t)$: Ramp-up completed production steps index using MES

To illustrate typical causes of excessive high/low completed steps during ramp-up, Table 9 provides more insight. These scenarios are reconstructed in consultation with shift leads and operators.

Figure 24 presents a spatiotemporal representation of the second example in Table 9. One can clearly observe the multiple spatial movements of a wafer box on the map containing several visits to M1. For example, a step that requires multiple visual inspections in between processing at M1. All these movements are captured by the RTLS. The MES does not capture this revisiting behavior. MES only registers a start and end time for this process step, but the RTLS

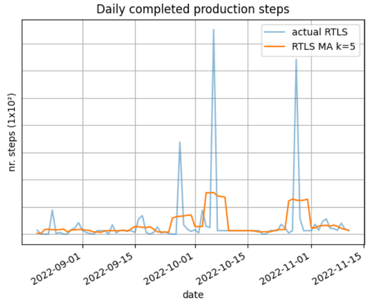


Fig. 22: $f_2(t)$ Completed production steps registered by RTLS

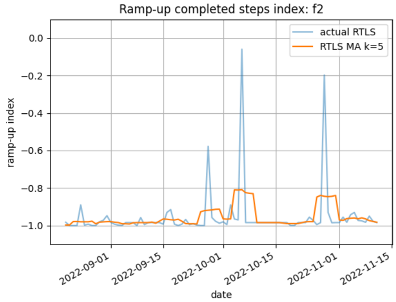


Fig. 23: $s_2(t)$: Ramp-up completed production steps index using RTLS

Table 9: Exemplification of scenarios contributing to completed production steps based on qualitative data

Event	Description
Incorrect communication	Engineers do not notify operators via MES, but via Teams/mail on lot status change, which corrupts the MES data.
Single step with revisit(s)	Workstation and PC are separated which causes multiple walks between PC and workstation for a single step, hence not all steps are registered by MES (Figure 24).
Missing waferbox	Wafer box could not be located

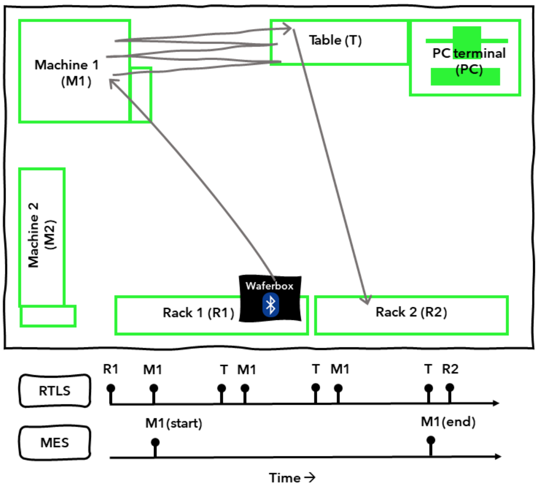


Fig. 24: RTLS vs MES example: single step with revisit(s)

data learns us that this duration consists of multiple runs at M1, transportation between M1 and T, and time spent at T.

6.3 Quality of products

The third ramp-up performance index $f_3(t)$ focuses on product quality. As mentioned in the introduction of this section this index was not covered by the RTLS and MES. It's straightforward to observe that an RTLS is not capable of capturing product quality with location data. Unfortunately, quality management was performed outside the MES in this case study.

6.4 Process time

The fourth ramp-up index $f_4(t, m)$, and the final performance index before the registration accuracy indices are presented, covering the process time of steps. This index focuses on the time a person or machine spends on a specific production step and it is registered by MES, but in theory, it can also be derived from RTLS data. Shorter and more consistent process times are associated with a mature and predictable ramp-up. MES data as of May 2021 is used and RTLS data was included as of August 2022. For sake of simplicity, this section only presents the average process time over all machines instead of the process time per machine.

Figure 25 and Figure 27 present the daily average process time for MES and RTLS respectively. It was decided to use SMA with $k = 5$ as a smoothing technique. Subsequently, Figure 26 and 28 present the transformed ramp-up indices for MES and RTLS respectively. This is the transformed result indicating how far the average process time index of production steps is removed from ramp-up completion. Similar to $f_2(t)$, this transformation is achieved by normalizing the average process time to a maximum daily process time established after discussion with production leads. Additionally, a transformation results in the index ranging from -1 to 0 indicating the distance to ramp-up completion.

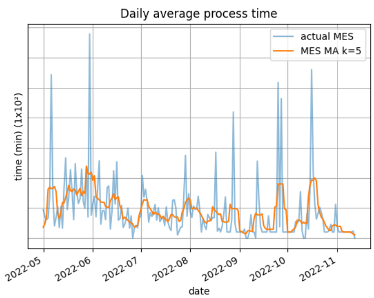


Fig. 25: $f_4(t, m)$ Average process time registered by MES

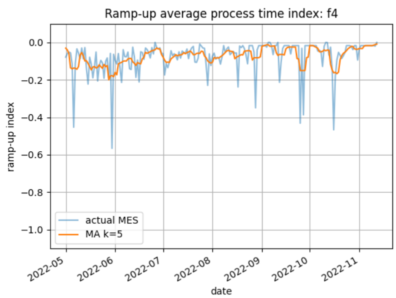


Fig. 26: $s_4(t)$: Ramp-up process time index using MES

Between May 2021 and November 2022 a slightly declining pattern of MES-registered process times can be seen in Figure 25 indicating the average

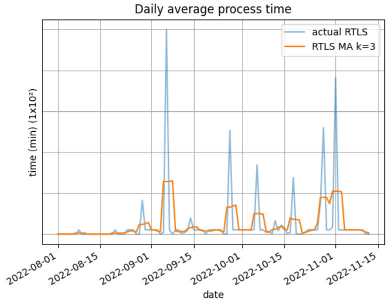


Fig. 27: $f_4(t, m)$ Average process time registered by RTLS

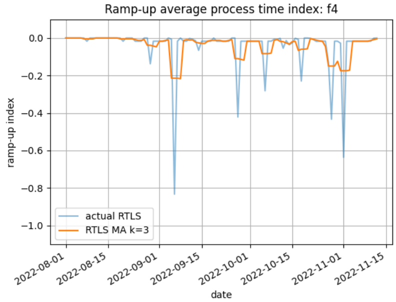


Fig. 28: $s_4(t)$: Ramp-up process time index using RTLS

process times of production steps are decreasing. This observation implies the process improves over time since on average less time is spent on similar production steps. A conceivable cause of this observation is the acquisition of new machines, which process wafers faster or in batches, which both reduce the average process time per wafer. However, the variation in the average process time seems to be perpetual. Occasionally high average process times are motivated by additional rework steps or the situation where the step is signed off at a later moment than the actual step end date.

Regarding the process times registered with the RTLS the average process time is short. Similar to MES the result contains significant peaks. After observing the operators it was concluded that sometimes the wafer transportation boxes are not stored near the machine but somewhere else (e.g. desk, storage rack, etc.). As a result, the RTLS only registers a short visit to the machine while in reality, the wafers are still in process.

Overall, it seems to be that the process time index for both MES and RTLS is close to ramp-up completion. However, one aspect that is not captured is the number of wafers in production. During the deployment, there were several decisions made by management, which reduced the WIP (e.g. to give priority to certain orders or to reduce the load on certain machines). It is straightforward that less WIP enables operators to process the wafers faster. Nevertheless, both indices contain spikes 2 to 4 times as high as the smoothed line. This hints on the negative impact of events on the process time. Since these events cannot be derived from these figures, Table 10 illustrates some scenarios resulting in excessive process times during ramp-up.

Figure 29 presents a spatiotemporal representation of the second example in Table 10. This example contains three production steps including visits to M2, M1, and M2 again respectively. By looking at the timeline one can observe that the RTLS was capable of capturing the timestamps of each visit. Yet, the same production steps captured by the MES are corrupted. The time related to the first visit to M2 is excessive, whereas the registered time for the other

Table 10: Exemplification of scenarios contributing to process time based on qualitative data

Event	Description
Missing resources	E.g. mask needed for production step could not be located
Corrupted time registration	(Experienced) operators can perform tasks based on experience, so do not use MES for every production step (Figure 29)
Excessive process time	Operator forgets to sign off step such that process time keeps accumulating

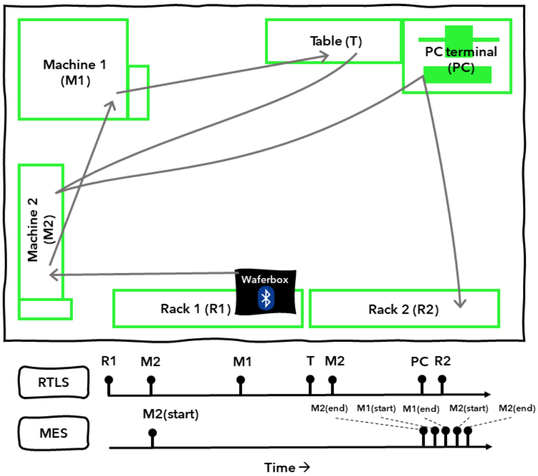


Fig. 29: RTLS vs MES example: corrupted time registration

two visits is unrealistically short. This is the consequence of allowing people to deviate from the MES.

6.5 Pathway deviations

The first ramp-up registration accuracy index, and fifth overall index, deals with the discrepancy of object locations. As stated in section 1, an RTLS is capable of revealing what is actually happening in our production process compared to what one 'thinks' is happening. Furthermore, an RTLS enabled us to look in real-time where and for how much time wafer boxes were positioned. It is assumed that an RTLS implemented in a mature and predictable production process is mimicking the object locations registered with an MES. In other words, this discrepancy fades out when coming closer to ramp-up completion. To quantify how accurately the actual production process is registered, $f_5(t)$ measures the registration accuracy of pathways. This is done by comparing pathways registered by the RTLS and MES. As explained in section 3.2.5 different techniques can be used to achieve this goal. For this specific case study, it was chosen to implement a Sørensen-Dice similarity. This similarity technique was chosen over an Euclidean distance since the layout of the cleanroom was U-shaped and consists of several 'smaller' areas. Using

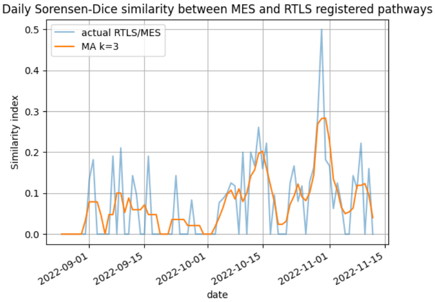


Fig. 30: $f_5(t)$ Sørensen-Dice similarity between MES and RTLS measured pathways

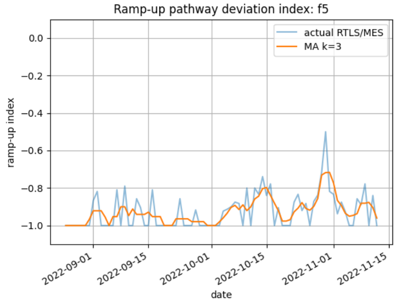


Fig. 31: $s_5(t)$: Ramp-up pathway deviation index

the shortest distance between machines results in unrealistic outcomes. The cosine similarity metric overcomes this issue because it compares the orientation of pathways. Still this metric was also neglected, since we were not able to capture all routes. In other words, only 20 workstations were provided with anchors. Ergo, the exact route between these workstations included additional steps, which were not analyzed in this work. The Sørensen-Dice and Jaccard similarity techniques resulted in similar results, but the former was preferred over the Jaccard similarity since it is less prone to the size of the data set. On beforehand it was expected that the size of the data sets would influence the result. In practice, this expectation was justified, because the RTLS data collected per month was 5 to 6 times larger compared to collected MES data in the same period. Moreover, the Sørensen-Dice similarity is also the most intuitive metric of all four as it calculates the percentage of overlap between sets of pathways collected with MES and RTLS.

Figure 30 presents the outcome of the Sørensen-Dice similarity of pathways. Since the RTLS was fully operational in August 2022 the similarity was calculated from that moment onward. The similarity ranges from 0 to 1 implying no similarity at all to a 1-on-1 similarity respectively. Additionally, it was decided to apply an SMA with $k = 3$ as a smoothing technique. Subsequently, the similarity values require a small transformation such that its values fit between a -1 to 0 scale where -1 implies no similarity at all and 0 a one-on-one relationship. The result is presented in Figure 31.

A first observation is the overall similarity values are low (< 0.5), indicating that pathways registered by MES are significantly dissimilar to pathways registered by the RTLS. On the 'best' day around 50% of the paths completed by wafer boxes are similar to the ones registered by the MES. In other words, the remaining 50% of the pathways is not overlapping with each other. Additionally, there are certain moments at which the similarity value is equal to 0 indicating 0 similarities between routes. Comparable to other indices, this can be explained that this index does not take into account the number of wafer boxes in production. Consequently, the index in Figure 31 indicates the registration accuracy is far from ramp-up completion. The overlap of locations, where wafer boxes have actually been versus registered locations, is minimal. Hence, the accuracy of registering is still immature and incomplete. To illustrate typical causes for the discrepancy among MES and RTLS registered pathways, Table 11 provides more insights. These examples are designed in consultation with shift leads and operators when discussing the results.

Table 11: Exemplification of scenarios contributing to pathway deviations based on qualitative data

Event	
Location hopping	Certain production steps are repeated at different locations. This results in extended pathways while MES does not register extra steps.
Room for error	Since operations can be performed without MES, operators will do so (un)intentionally resulting in additional pathways.
Incorrect storage	Sometimes batches are not stored away after processing (or taken to an external location) such that its path might deviate from it's expected path (Figure 32).

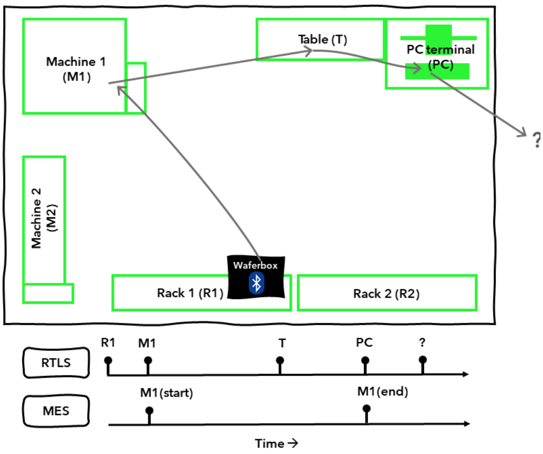


Fig. 32: RTLS vs MES example: incorrect storage

Figure 32 presents a spatiotemporal representation of the third example in Table 11. This example contains a single process step visiting M1. The MES data captures the start and end time of this step, which is all it is capable of in this case. Based on internal agreements the wafer box should be stored in R2 after finishing this process step. Looking at the RTLS timeline we do observe that the wafer box visits T and PC after being processed on M1. But more important, is the fact that after signing off the step in MES at the PC the wafer box is not stored at R2. Since the proposed RTLS implementation does not

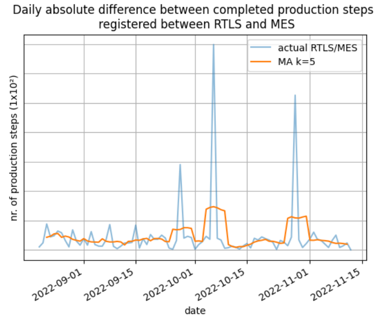


Fig. 33: $f_6(t,m)$ Registration accuracy of completed production steps registered by RTLS and MES

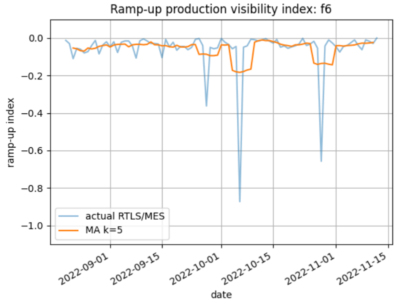


Fig. 34: $s_6(t)$: Ramp-up production visibility index

cover the entire cleanroom it could be that the wafer box is in a blind spot of the RTLS. However, based on qualitative information it also happens that wafer boxes are incorrectly stored or taken by engineers. In short, the MES implies that this wafer box must be at R2, while in reality, its location is unknown potentially resulting in excessive search times, unnecessary communication or 'worst case scenario': a lost wafer box.

6.6 Production visibility

The sixth ramp-up index $f_6(t,m)$ presents the registration accuracy of completed production steps at each machine: the production visibility. Whereas $f_5(t)$ looked at the registration accuracy of pathways through the factory, this index looks at how many steps are performed versus how many steps are registered? Figure 33 presents the result for $f_6(t,m)$. SMA with $k=5$ was selected as the smoothing technique. Additionally, the result of $f_6(t,m)$ is transformed such that it fits the ramp-up index conditions ranging from -1 to 0; indicating the distance from ramp-up completion. The transformed result ($s_6(t)$) was achieved by normalizing the deviation of registered production steps concerning a maximum capacity of production steps per day established after discussion with production leads.

First and foremost, apart from the three peaks, it appears that the difference between completed steps registered by MES and RTLS is minimal. Furthermore, the difference is stable over time. This stable behavior is especially reflected in the smoothed SMA for a relatively low value for k. Although the difference is small, its origin was still investigated. It was concluded that certain subsequent steps are executed at the exact same location which does not trigger the RTLS. As a result, fewer production steps are registered by the RTLS. Secondly, the three peaks are all single-day observations. Meaning 'something' happened on this day which increased the number of registered production steps outside the 'eye' of the MES. This exceptional behavior is in line with observations from researchers and engineers. For example, the fact that a certain production step is not correctly implemented in MES enabling the operator to walk back and forth between two machines without MES registering these 'movements'. Nevertheless, it is expected that this behavior is observed more frequently instead of three times only. After discussion with shift leads and observations in the clean room, no sound motivation was found to explain these differences in registered production steps. The only explanation which could not be ruled out is the effect of replacing anchors and/or beacons throughout the deployment during the inspection of the RTLS. Overall the registration accuracy index of production visibility in Figure 34 indicates the accuracy of registering production steps is close to ramp-up up. This might seem confusing since $s_2(t)$, which looked at the number of completed production steps, is far from ramp-up completion. However, $f_2(t)$ looks at the number of completed steps, whereas $f_6(t, m)$ covers the registration accuracy. When combining these indices, one could state that on the one hand, the number of completed production steps is insufficient (production capacity is underutilized). On the other hand, the registration of completed production steps is mature since the difference between what is registered and what is actually happening on the shop floor is small.

Table 12 discusses some of the frequently occurring events related to deviations between production steps registered with an MES and RTLS. These events are designed based on observations inside the cleanroom.

Table 12: Exemplification of scenarios contributing to production visibility based on qualitative data

Event	Description
Immature MES	Steps in the MES are not implemented in enough detail enabling operators to perform production steps outside of MES (Figure 35).
External production step	Handful (crucial) production steps are performed at an external location
Out of cleanroom	Engineer takes a batch to grey room or his/her desk.

Figure 35 presents a spatiotemporal representation of the first example in Table 12. This example contains a single production step at M1. MES registered the start and end date of this step, but the RTLS implies an additional visit to M2. Without additional information, it must be assumed this extra step was deemed necessary. Nevertheless, potentially valuable information about this extra step at M2 is lost if MES is not able to capture it. This is the result of an MES that is, similar to the production process itself, continuously expanding and evolving along the ramp-up. Even though such scenarios are imminent the production data generated at M2 can be of use for product or process-related issues regarding the ramp-up.

6.7 Production traceability

The seventh and final ramp-up index ($f_7(t, m)$) quantifies the difference in registered process time per step and actual time spent at the workstation.

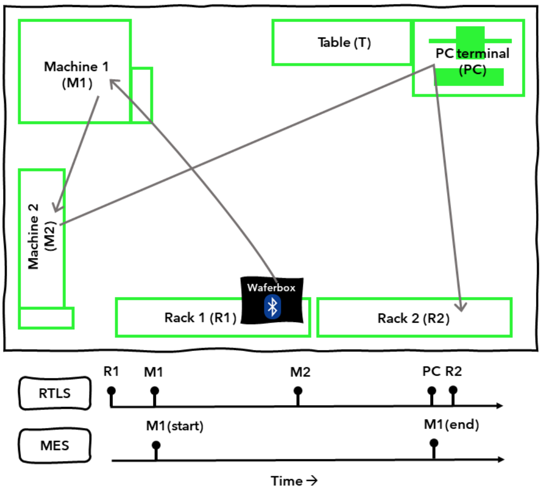


Fig. 35: RTLS vs MES example: immature MES

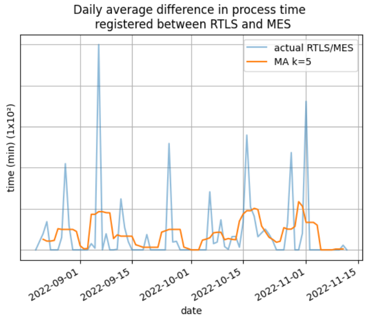


Fig. 36: $f_7(t,m)$ Registration accuracy of production time registered by RTLS and MES

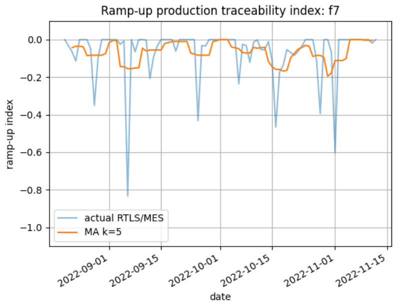


Fig. 37: $s_7(t)$: Ramp-up production traceability index

This difference is considered an indicator of production traceability. Again, MES data as of May 2021 is used and RTLS data was included as of August 2022. For sake of simplicity, only the difference in average process time over all selected workstations is presented. Figure 36 presents the average difference in process time of each production step registered between MES and RTLS. It was decided to use SMA as a smoothing technique with a $k = 5$ since no clear underlying trends were visible. Afterward, the result is transformed to $s_7(t)$, which is presented in Figure 37. Similar to $s_3(t)$, this transformation is achieved by normalizing the average process time with respect to a maximum value of process time (in min) established after discussion with production leads.

The results of the production traceability learns us the following: Firstly, on certain days there is a difference in the order of 10^2 minutes which cannot be traced by the MES. After discussing the results with engineers and operators, numerous reasons are motivating this difference. For example, operators who forget to sign off a step in MES result in unrealistic process times. For a total of 20 workstations, this is acceptable. The exceptions of a few hundred minutes on certain days are in line with reality. Secondly, Figure 36 also reveals periods for which the difference between registered and actual process times is minimal or even close to zero. Looking back to $f_2(t)$ and $f_4(t, m)$ this observation has a similar explanation i.e. low WIP. If $f_2(t)$ and $f_4(t, m)$ are not taking into account the WIP so will this index. In other words, differences in registered process times are typically low, because there is not much WIP inside the production process. The third interesting observation is that the peaks do not have the same location as the peaks of the previous index in Figure 33 indicating that days when a lot of production steps happen outside of the MES it does not necessarily result in an excessive lack of production visibility. In other words, these steps are often short production steps. Overall, the accuracy of registering process time is insufficient. In contrast to the previous index ($f_6(t, m)$), the registration accuracy index for production traceability is varying a lot. Although $s_7(t)$ appears to be close to ramp-up completion this is mainly due to periods with low WIP. Specifically, the significant peaks indicate the lack of traceability for certain periods.

Table 13 elaborates on reoccurring scenarios throughout the process effecting the production traceability. These scenarios are identified after going through the RTLS data together with shift leads and operators.

Table 13: Exemplification of scenarios contributing to production traceability based on qualitative data

Event	Description
Excessive process times	An operator or engineer might forget to sign off a step in MES causing excessive process times. Especially if there is no subsequent shift (during night or weekend) this affect the process times a lot.
Leave wafer box at workstation	operators are not forced to store boxes away and therefore tend to forget to put it back or leave it there when taking a break.
Experience operators	experience operators know certain processes by heart. Therefore they tend to perform all steps and do the 'administration' as they call it later in MES causing unrealistic process times.

Figure 38 presents a spatiotemporal representation of both the first and second examples in Table 13. This example contains a production step with a visit to M1. After being processed on M1 the wafer box is put at a table as can be derived from the RTLS timeline. What happens next remains unclear. Based on the MES data the step is still in production but based on observations and consultations with operators, the wafer box is left at T because it was time for a break or accidentally forgotten to sign off in MES resulting in unrealistic process times registered by the MES.

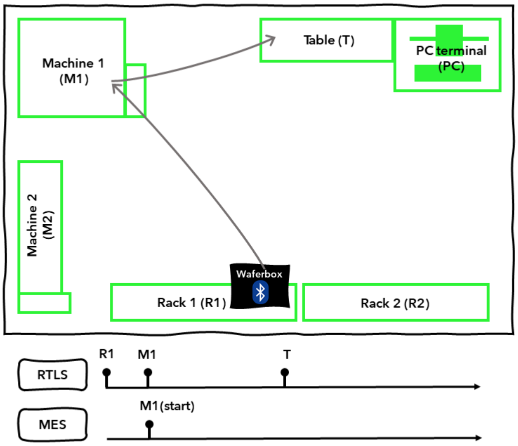


Fig. 38: RTLS vs MES example: single step, multiple locations

6.8 Overall ramp-up metric

Given the calculated ramp-up indices (four performance indices and three registration accuracy indices), the overall ramp-up index can be calculated as explained in section 3.7. Similar to (Doltsinis et al., 2013) the individual ramp-up indices are transformed to the same scale to enable the aggregation into one single overall ramp-up metric. However, where Doltsinis et al. (2013) used this overall ramp-up metric to asses the ramp-up progress of one single robotic arm, this work aims to assess the overall ramp-up performance of a job shop. For this case study, the individual contribution of each ramp-up index was considered equal. Meaning, weights $\alpha_1, ..., \alpha_7$ were all equal to 1.

$$
\begin{aligned}
(i) f_{overall}(t) = s_1(t) + s_2(t) + s_4(t, m)\\
\text{s.t.}\\
min = -3.0\\
max = 0.0
\end{aligned}
$$

$$
\begin{aligned}
(ii) f_{overall}(t) = s_1(t) + s_2(t) + s_4(t, m) + s_5(t) + s_6(t, m) + s_7(t, m)\\
\text{s.t.}\\
min = -6.0\\
max = 0.0
\end{aligned}
$$

The challenge during ramp-up is that production processes are ill-understood. To answer our research question the overall ramp-up index is calculated twice: (i) once with indices that can be calculated using MES data.

(ii) once with indices using also indices based on RTLS data. The answer if RTLS can contribute to ramp-up performance measurement lies in the difference between (i) and (ii). The overall ramp-up index is not calculated solely on RTLS data. This would conflict with our assumption of the need for an MES. Mathematically this results in the following two overall ramp-up indices for (i) and (ii) respectively.

Both overall ramp-up indices (i) and (ii) are presented in Figure 39 and 40 respectively. Recall that the model requires two parameters to indicate the start of the ramp-up completion zone and the end of the start ramp-up zone (Table 7). It was decided to set these model parameters λ_1 and λ_2 equal to 1/3, and 2/3 of the minimum ramp-up value. This was based on discussions with operations managers.

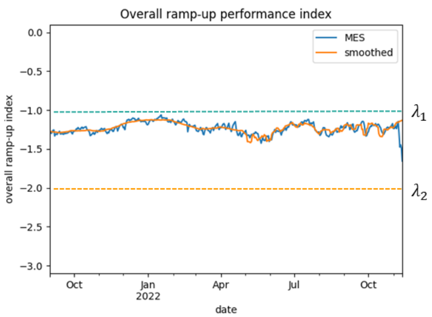


Fig. 39: $f_{overall}(t)$ based on MES data

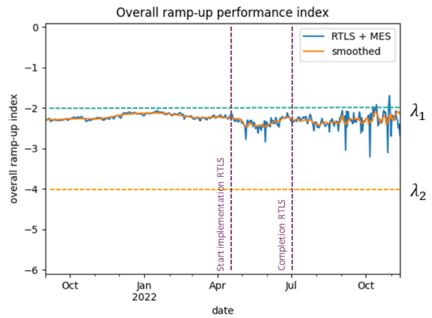


Fig. 40: $f_{overall}(t)$ based on RTLS and MES data

Since both overall-ramp-up indices have an unequal number of individual ramp-up indices the minimum value of the index is different. As explained above, the result in Figure 39 is based on three indices, hence the minimum value of 3×-1, whereas the result in Figure 40 is based on six indices, hence the minimum value of 6×-1. Moreover, the RTLS was implemented at a later stage. The start and end of the implementation are visualized in Figure 40 by the purple lines.

Without taking into account the RTLS, Figure 39 presents an undulating ramp-up behavior. Over a period of 12 months (October 2021 until October 2022) this behavior is unchanged. However, around November 2022 a significant drop is observed. This drop is mainly caused by $s_1(t)$ (production disruptions) due to the downtime of critical machines to enable the transition from 3- to 4-inch wafers. This decision by production managers also affected some of the other indices contributing to this observation in the overall ramp-up index. According to the three basic ramp-up stages presented in Table 7, the ramp-up performance based on MES data has passed the stage of 'start ramp-up' and is currently in the stage of 'ramping up'.

Secondly, the overall ramp-up performance index in Figure 40, including MES and RTLS data, reveals additional information. Up until April 2022, the result is the same. Between the start and completion of the RTLS implementation, the result shows some deviations related to the introduction of the RTLS. Nevertheless, we focus only on the period after the RTLS is completely implemented as of August 2022. First of all, although the smoothed result does not reveal a lot, multiple downward-faced peaks of the performance index can be observed in the actual results (blue line). These are mostly caused by registration accuracy indices $s_6(t,m)$ and $s_7(t,m)$. This observation illustrates the lack of visibility and traceability of the production process during ramp-up. Between the introduction of the RTLS and the end of the deployment, the overall ramp-up performance is positioned closely below the λ_1 threshold, and sometimes even exceeding λ_1 it for a short period. Moreover, the combined result of MES and RTLS data hints at the arrival of a new stage in the ramp-up. From 'ramping up' the production process is transitioning into a new stage of 'ramp-up completed'. This transition is not visible without collecting the real-time position data.

All in all, according to the proposed ramp-up performance measurement framework, SMART Photonics is amid the ramp-up stage. From interviews with management and experts on sight, this resembles the current status of their 'Lab to Fab' transition. The smoothed overall ramp-up index does not show a clear difference between RTLS and MES data, while this difference in the individual indices is more abundant. This might have to do with accounting for different weights per ramp-up index. As mentioned, for this study we set all weights $\alpha_1, \ldots, \alpha_7$ equal to 1. Nonetheless, adding the registration accuracy indices, leveraging RTLS data, provides additional information to the overall index. For example, the fluctuations caused by the immediate result of discrepancies between what MES and RTLS are registering. Without looking into the responsible individual index these fluctuations cannot be clearly allocated by looking solely to the overall performance index.

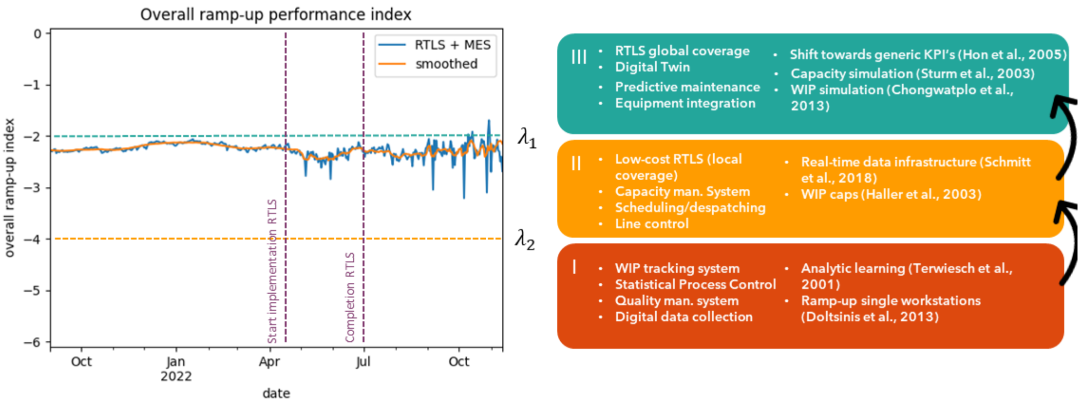


Fig. 41: Ramp-up performance managerial implications

The goal of this work was not only to quantify early-stage ramp-up performance, but also to enable companies to accelerate ramp-up such that they secure their mission toward mass manufacturing. As such the final step of the proposed ramp-up performance measurement framework is 'Evaluate and learn' (Figure 4). The aim here is to connect novel ramp-up management approaches (Schmitt et al., 2018) to the experience gained throughout this research to contribute to the field of future ramp-up. As a result, Figure 41 connects recommendations of ramp-up performance, job shop, and Industry 4.0-related literature to the degree of ramp-up. With this Figure we conclude the results by providing a tangible road map for production companies based on our experience and related work discussed in section 2.

For each of the three ramp-up phases, some potential stepping stones are provided on the right-hand side of Figure 41. The approaches of the existing literature are assigned to a stage based on characteristics per ramp-up stage presented in Table 7. The other stepping stones are based on expert interviews with production managers inside the company as well as academic experts within the field of manufacturing systems. It must be stated these stepping stones are subjective and should be supported by additional research within this field. Nonetheless, given the literature and interviews, we are confident that these elements are useful stepping stones to lead a job shop type of production process through ramp-up.

7 Discussion

Quantifying production performance during an unpredictable and ill-understood period may never be fully accurate. Also the proposed low-cost RTLS does not reveal all hidden elements that an MES can not capture. Nonetheless, we are confident the proposed performance measurement framework and RTLS contribute to a better understanding of the ramp-up. This section critically discusses how the framework and RTLS can be improved as well as their limitations.

This work acknowledges the fact that the framework is limited to performance indicators, which can be measured with the existing MES and proposed RTLS. As mentioned, the selected data sources are not (yet) capable of capturing the quality of products throughout the ramp-up. While this is still considered an important metric during (and after) ramp-up, our results are impacted by its absence and could be improved by including this index in the future.

One potential flaw of the proposed framework is not taking into account the time horizon of a typical ramp-up when selecting a case study. Especially for our chosen case study, it is difficult to interpret the results. Historical ramp-ups of semiconductor manufacturers could take a few years up to a decade. With only 18 months of MES data and 4 months of RTLS data, it is difficult to draw conclusions on long-term ramp-up behavior.

Moreover, the impact of an individual ramp-up index on the overall ramp-up index is visible. For example, the peak in production disruptions ($f_1(t)$) in Figure 19 is present in the overall ramp-up index (Figure 39). These are no outliers since they could be motivated by contextual information with help of engineers, shift leads, and/or operators. However, the consequence of this current design is that the overall ramp-up index contains a lot of variation. Currently, the effect of such fine-scaled structures is tackled by smoothing techniques. Perhaps this could be improved by introducing different levels for the ramp-up performance measurement framework. For example, a level for which the individual ramp-up indices are assessed for daily review and a more strategic level which excludes such fine-scaled structures.

Another aspect that the proposed framework does not take into account is the stability of indices. According to Doltsinis et al. (2013) reaching consistency in output is of more significance than a one-off good result. The current design of the ramp-up indices does account for the accuracy of registering performance, but not for variability. Rewarding stability (or penalizing variability) could contribute to better ramp-up performance management.

Regarding the design of the proposed RTLS, many improvements can be made to compete with industry standards. For example, the energy efficiency of anchors and beacons, including 3D localization instead of 2D, and the use of more advanced localization techniques to increase the accuracy of positions. However, the goal of this work was not to outperform existing RTLS solutions, but rather to investigate the potential of a low-cost solution for manufacturers during ramp-up.

Concerning the implementation of the proposed RTLS, there are a few limitations. Due to the densely populated cleanroom and confidence of the positioning engine, it takes the RTLS between 20 and 120 seconds to verify a change in position. This window is considered 'near real-time'. Furthermore, in our case study, only 20 workstations were considered. The limitation of not having global coverage resulted in 'blind spots' objects if none of the anchors picked up a signal of a beacon. This could be solved by adding more anchors. However, the required budget and time to achieve this were not allocated to this case study.

Throughout the deployment, a few external factors influenced the desired quantity of the collected data. One factor was a decision to reduce the WIP to give priority to a limited set of orders. This had a great impact on the number of wafer boxes we were tracking during the deployment. Secondly, during the deployment, several scheduled maintenance activities of critical machines put some orders on hold. Hereby, the activity inside the cleanroom was reduced, impacting our results as well. On the other hand, these factors are also exactly what characterizes the ramp-up.

8 Conclusion

The goal of this work was to contribute to adequate performance measurement of an early-stage ramp-up in job shop-type manufacturing environments. The shift of high-tech production companies from time-to-market to time-to-volume during the 00s, puts the tail end of the ramp-up in a critical position. Simultaneously, the rise of IoT in manufacturing increases the number of low-cost sensors in manufacturing environments boosting the next industrial revolution. Combining both developments, this work explored whether an RTLS can contribute to ramp-up performance measurement of job shops.

As a result, we proposed a framework for measuring the ramp-up performance. The framework is inspired by the rise of IoT in manufacturing and builds upon the single workstation ramp-up performance framework designed by Doltsinis et al. (2013). To support this framework with real-time production data, this work introduces an information system architecture containing a low-cost and scaleable RTLS alongside an existing MES. During ramp-up, when existing performance measurements (cost, flexibility, quality, and time) are not always applicable yet, the framework demonstrates its capability of real-time ramp-up performance measurement. Seven multi-dimensional indicators have been identified to quantify the ramp-up performance and registration accuracy of a job shop. Four indices covered the ramp-up performance by measuring production disruptions, product quality, completed production steps, and process times. The remaining three indices covered the accuracy of registering production data by measuring pathway deviations, production visibility, and production traceability.

As a result of this (near) real-time insight into ramp-up performance, the overall ramp-up performance indicates the distance removed from ramp-up completion. Furthermore, we divided the total ramp-up into three different stages. Concrete recommendations based on our results serve as stepping stones throughout each stage, connecting the overall ramp-up performance index to existing ramp-up approaches in the literature and managerial implications. To the best of our knowledge, the proposed framework is unique for ramp-up performance measurement within a job shop, but also the first to leverage real-time location information to quantify ramp-up performance.

In essence, the implementation of the proposed framework and RTLS within the case study resulted in observations in line with earlier research. The RTLS resulted in better traceability of wafer boxes and increased visibility of production steps. However, these findings were expected, because these have been demonstrated in earlier work. The proposed framework aimed at revealing the discrepancy between what one ‘thinks’ is happening in their production process and what is actually happening to improve ramp-up decisions. For five indices we reconstructed multiple scenarios resulting in a slower ramp-up based on data collected by the RTLS. Lastly, the overall ramp-up index also answers a more strategic question ‘how far are we from ramp-up completion?’ A rewarding observation is the undulating behavior of the overall ramp-up metric, which is conceptually illustrated in several earlier research, but is now approached quantitatively.

All in all, using a low-cost and scaleable RTLS during ramp-up has demonstrated its usefulness in improving ramp-up performance measurement by revealing the unseen. Additionally, the automated collection of real-time positions of objects is undoubtedly the next step in the industrial revolution However, it is important to note that an RTLS should not be the only source of information used as input for ramp-up performance measurement. Towards the end of ramp-up, when production becomes less R&D-based and more stable, the production process automatically becomes prone to generic factory physics. In other words, a proper MES must be in place by then. The question if RTLS will play a role in an established job shop has already been identified, but how real-time location data can be used even more in performance measurement of job shops is to be determined in future work.

To conclude this work the following suggestions for future work are considered.

Cross-validation of the proposed framework must confirm the suitability of the framework for job shops in ramp-up for other industries than the semiconductor industry. As soon as this has been confirmed and more data is collected, future work could focus on extending the framework with a predictive layer: projecting the future ramp-up performance based on the individual indices.

Secondly, given the development of the Industry4.0 concept and and increasing number of sensors in manufacturing environments, we assume the quality of an RTLS will increase while the economy of scale will reduce its costs. Future work is in line with this assumption. The RTLS will continue to collect data, opening new doors for future research.

Similar to Thiesse et al. (2006), factory layouts can be designed using real-time location data. Another possibility could be designing dispatching rules or queue priorities based on locations. Fourthly, the period from ramp-up start to end is still ill-understood, while high-tech production companies experience a shift from time-to-market to time-to-volume. On that account, to better position existing ramp-up approaches thorough research on different sub-phases inside the ramp-up transition is required.

Regarding the implementation at SMART Photonics, it was chosen to start looking into intertwining the MES and RTLS more through integration of the beacons inside an electronic label. This is a beacon combined with an e-paper display that presents live information from the MES. The regular paper-based system could then be replaced as well. Also, it was decided to explore the expansion of the RTLS within the current facilities.

Acknowledgments. The author would like to thank all employees at SMART Photonics for their cooperation, their willingness to exchange ideas, and the opportunity to be part of their 'Lab to Fab' journey. In particular André van de Geijn for his guidance and expertise.

In addition, the author would like to express his gratitude to his supervisors from Eindhoven University of technology. Especially Alp Akçay for over 40 fruitful mentor meetings of which each and every meeting contributed to new insights and improvements. Moreover, the fanaticism of Ivo Adan for exploring new ideas combined with arranging a field trip as well as financial support of the OPAC group contributed significantly to the quality of this work. Also, the author would like to thank Remco Dijkman for taking the time to review this work as 3rd assessor. Apart from the supervision, the author acknowledges the external support from Indutrax GmbH and Alltrons BV. Thanks to Hans-Gerd for providing the Indutrax Application Environment and additinonal support to make the analysis of our RTLS possible. Last but not least, Kayle Knops from Alltrons BV. Thank you for your technical advice and support whenever we got stuck.

References

Akter, S., Patwary, J.A., Akter, S., Nahar, L. (2014). *An Efficient Travel Time Prediction Method using Cosine Similarity* (Tech. Rep.). Retrieved from www.ijert.org

ANSI/ISA (2000). *ANSI/ISA 95.00.01-2000, Enterprise-Control System Integration.*

Ariane Hellinger, & Heinrich Seeger. (2011). *Cyber-Physical Systems Driving force for innovation in mobility, health, energy and production* (Tech. Rep.). ACATECH – National Academy of Science and Engineering. Retrieved from www.acatech.de

Arkan, I., & Van Landeghem, H. (2013). Evaluating the performance of a discrete manufacturing process using RFID: A case study. *Robotics and Computer-Integrated Manufacturing*, *29*(6), 502–512.

10.1016/j.rcim.2013.06.003

Ball, P.D., Roberts, S., Natalicchio, A., Scorzafave, C. (2011, 6). *Modelling production ramp-up of engineering products* (Vol. 225) (No. 6). 10.1177/09544054JEM2071

Benfer, R.H. (1993). *Learning during ramping Policy choices for semiconductor manufacturing MS Thesis MIT* (Unpublished doctoral dissertation). Massachusetts Instutute of Technology, Cambridge MA.

Bohn, R.E. (1995). Noise and learning in semiconductor manufacturing. *Management Science*, *41*(1), 31–42.

10.1287/mnsc.41.1.31

Bradbee, G.R., Gates, K.B., Wilcox Jr., R.B. (1989). Early manufacturing involvement in new process technology. (pp. 12–16).

Brown R.G. (1959). Statistical forecasting for inventory control.

Broy, M., Geisberger, E., Cengarle, M.V., Keil, P., Niehaus, J., Thiel, C., Thönnißen-Fries, H.-J. (2011). Cyber-Physical Systems-Innovationsmotor für Mobilität, Gesundheit, Energie und Produktion,”. *acatech–Deutsche Akademie der Technikwissenschaften (Hrsg.), acatech Position Dezember*.

Chongwatpol, J., & Sharda, R. (2013). RFID-enabled track and traceability in job-shop scheduling environment. *European Journal of Operational Research*, *227*(3), 453–463.

10.1016/j.ejor.2013.01.009

Clark, K.B. (1991). *Product development performance : strategy, organization, and management in the world auto industry.* Boston, Mass.: Harvard Business School Press.

Doltsinis, S.C., Ratchev, S., Lohse, N. (2013, 8). A framework for performance measurement during production ramp-up of assembly stations. *European Journal of Operational Research*, *229*(1), 85–94.

10.1016/j.ejor.2013.02.051

Fjällström, S., Säfsten, K., Harlin, U., Stahre, J. (2009). Information enabling production ramp-up. *Journal of Manufacturing Technology Management*, *20*(2), 178–196.

10.1108/17410380910929619

Flaherty, M. (1990). Managing manufacturing and engineering in VLSI fabs. (pp. 17–20).

Friis, H.T. (1946). A Note on a Simple Transmission Formula. *Proceedings of the IRE*, *34*(5), 254–256.

10.1109/JRPROC.1946.234568

Gladysz, B., & Santarek, K. (2017). An approach to RTLS selection. *24th international conference on production research, icpr 2017* (pp. 13–18). DEStech Publications. 10.12783/dtetr/icpr2017/17576

Glick, M., Abrams, N., Cheng, Q., Teh, M.Y., Hung, Y.-H., Jimenez, O., … Bergman, K. (2020, 1). PINE: Photonic Integrated Networked Energy efficient datacenters (ENLITENED Program) [Invited]. *Journal of Optical Communications and Networking*, *12*, 443.

10.1364/JOCN.402788

Haller, M., Peikert, A., Thoma, J. (2003). *Cycle time management during production ramp-up* (Vol. 19; Tech. Rep.). Retrieved from http://www.infineon.com.

Hentz, J.B., Nguyen, V.K., Maeder, W., Panarese, D., Gunnink, J.W., Gontarz, A., … Hascoët, J.Y. (2013). An enabling digital foundation towards smart machining. *Procedia cirp* (Vol. 12, pp. 240–245). Elsevier B.V. 10.1016/j.procir.2013.09.042

Holt, C.E. (1957). Forecasting seasonals and trends by exponentially weighted averages . *O.N.R. Memorandum*, *52*.

Hon, K.K.B. (2005). *Performance and Evaluation of Manufacturing Systems* (Tech. Rep.).

Huang, G.Q., Zhang, Y.F., Jiang, P.Y. (2008, 3). RFID-based wireless manufacturing for real-time management of job shop WIP inventories. *International Journal of Advanced Manufacturing Technology*, *36*(7-8), 752–764.

10.1007/s00170-006-0897-4

Huang, S., Guo, Y., Zha, S., Wang, F., Fang, W. (2017, 1). A Real-time Location System Based on RFID and UWB for Digital Manufacturing Workshop. *Procedia CIRP*, *63*, 132–137.

10.1016/J.PROCIR.2017.03.085

ISO (2014). *ISO/IEC 24730-1:2014 Information technology — Real-time locating systems (RTLS)* .

Jaccard, P. (1912). The distribution of the flora in the alpine zone. *New Phytologist*, *11*(2), 37–50. Retrieved from https://nph.onlinelibrary.wiley.com/doi/abs/10.1111/j.1469-8137.1912.tb05611.x

https://doi.org/10.1111/j.1469-8137.1912.tb05611.x

Jansen-Vullers, M.H., Kleingeld, A., Jansen-Vullers, M.H., Loosschilder, M.W.N.C., Kleingeld, P.A.M., Reijers, H.A. (2007). *Predictors of academic performance of engineering students View project Learning Analytics in Blended Learning View project* (Tech. Rep.). Retrieved from https://www.researchgate.net/publication/228613274

Kang, H.S., Lee, J.Y., Choi, S., Kim, H., Park, J.H., Son, J.Y., . . . Noh, S.D. (2016, 1). Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing - Green Technology*, *3*(1), 111–128.

10.1007/s40684-016-0015-5

Keith, C.K. (1996). *Accelerating Time-to-Money for a Semiconductor Wafer Fab Capacity Ramp* (Unpublished doctoral dissertation).

Khakifirooz, M., Fathi, M., Wu, K. (2019). Development of Smart Semiconductor Manufacturing: Operations Research and Data Science Perspectives. *IEEE Access*, *7*, 108419–108430.

10.1109/ACCESS.2019.2933167

Klaus Schwab (2015, 12). *The Fourth Industrial Revolution What It Means and How to Respond.*

Koutra, D., Parikh, A., Ramdas, A., Xiang, J. (2011). *Algorithms for Graph Similarity and Subgraph Matching* (Tech. Rep.).

Lars Mönch, John W. Fowler, Scott J. Mason. (2013). *Production Planning Control for Semiconductor Wafer Fabrication Facilities.*

Leachman, R.C. (2002). *Competitive Semiconductor Manufacturing: Final Report on Findings from Benchmarking Eight-inch, sub-350nm Wafer Fabrication Lines* (Tech. Rep.).

Liberti, L., & Lavor, C. (2017). *Euclidean Distance Geometry: An Introduction.* Springer.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., … Ueda, K. (2016). Cyber-physical systems in manufacturing. *CIRP Annals*, *65*(2), 621–641.

10.1016/j.cirp.2016.06.005

Müller, J., & Potters, L. (2019). *Future technology for prosperity : Horizon scanning by Europe's technology leaders* (Tech. Rep.). Retrieved from https://op.europa.eu/en/publication-detail/-/publication/ae785b63-dba9-11e9-9c4e-01aa75ed71a1 doi/10.2777/187237

Nian, L., Guo, Y., Wei, F., Jiang, J., Yuan, L. (2014). *A NEW RFID-BASED RTLS FOR DISCRETE MANUFACTURING WORKSHOP* (Tech. Rep.). Retrieved from http://asmedigitalcollection.asme.org/MSEC/proceedings-pdf/MSEC2014/45806/V001T05A006/4425643/v001t05a006-msec2014-3944.pdf

Nof S. Y. (2019). *Springer Handbook of Automation.*

NXP (2014). *The production of semiconductor chips* (Tech. Rep.). Retrieved from www.nxp.com

Pawellek, G. (2014). *Ganzheitliche Fabrikplanung: Grundlagen, Vorgehensweise, EDV-Unterstützung.* Springer -Verlag.

Poess, M., & Nambiar, R.O. (2008, 8). Energy Cost, the Key Challenge of Today's Data Centers: A Power Consumption Analysis of TPC-C Results. *Proc. VLDB Endow.*, *1*(2), 1229–1240. Retrieved from https://doi.org/10.14778/1454159.1454162

10.14778/1454159.1454162

Qiu, R.G., & Zhou, M.C. (2004, 3). *Mighty MESs* (Vol. 11) (No. 1). 10.1109/MRA.2004.1275947

Rácz-Szabó, A., Ruppert, T., Bántay, L., Löcklin, A., Jakab, L., Abonyi, J. (2020, 11). Real-time locating system in production management. *Sensors (Switzerland)*, *20*(23), 1–22.

10.3390/s20236766

Rajkumar, R., Lee, I., Sha, L., Stankovic, J. (2010). *Cyber-Physical Systems: The Next Computing Revolution* (Tech. Rep.).

R.C. Leachman (1996). Competitive semiconductor manufacturing survey: third report on the results of the main phase. *Berkeley Report*, *CSM-31*(Chapter 2).

Roberts, D.W. (1986). *Ordination on the basis of fuzzy set theory** (Vol. 66; Tech. Rep.).

Rodas, J., Barral, V., Escudero, C.J. (2013). Architecture for multi-technology real-time location systems. *Sensors (Switzerland)*, *13*(2), 2220–2253.

10.3390/S130202220

Schmitt, R., Heine, I., Jiang, R., Giedziella, F., Basse, F., Voet, H., Lu, S. (2018, 11). On the future of ramp-up management. *CIRP Journal of Manufacturing Science and Technology*, *23*, 217–225.

10.1016/j.cirpj.2018.03.001

SEMI (2021). *SEMI E10 - Specification for Definition and Measurement of Equipment Reliability, Availability, and Maintainability (RAM) and Utilization.*

Smith, N. (2021, 6). *How to Win the Global Battle for Microchip Dominance.* Retrieved from https://www.bloomberg.com/opinion/articles/2021-06-14/how-to-win-the-global-battle-for-microchip-dominance

Sturm, R., Dorner, J., Reddig, K., Seidelmann, J. (2003). Simulation-based evaluation of the ramp-up behavior of waferfabs. *Asmc (advanced semiconductor manufacturing conference) proceedings* (Vol. 2003-January, pp. 111–117). Institute of Electrical and Electronics Engineers Inc. 10.1109/ASMC.2003.1194478

Tao, Y., Both, A., Silveira, R.I., Buchin, K., Sijben, S., Purves, S., … Duckham, M. (2021). *A comparative analysis of trajectory similarity measures* (Tech. Rep.).

Terwiesch, C., & Bohn, R.E. (2001). Learning and process improvement during production ramp-up. *Int. J. Production Economics*, *70*, 1–19.

Terwiesch, C., Bohn, R.E., Chea, K.S. (2001). International product transfer and production ramp-up: A case study from the data storage industry. *R and D Management*, *31*(4), 435–451.

10.1111/1467-9310.00230

Thiede, S., Sullivan, B., Damgrave, R., Lutters, E. (2021). Real-time locating systems (RTLS) in future factories: Technology review, morphology and application potentials. *Procedia cirp* (Vol. 104, pp. 671–676). Elsevier B.V. 10.1016/j.procir.2021.11.113

Thiesse, F., Fleisch, E., Dierkes, M. (2006). LotTrack: RFID-based process control in the semiconductor industry. *IEEE Pervasive Computing*, *5*(1), 47–53.

Toro, C., Wang, W., Akhtar, H. (2021). *Implementing Industry 4.0, The Model Factory as the Key Enabler for the Future of Manufacturing.* Intelligent Systems Reference Library 202. Retrieved from http://www.springer.com/series/8578

Trauer, J., Schweigert-Recksiek, S., Engel, C., Spreitzer, K., Zimmermann, M. (2020). What is a Digital Twin? - Definitions and insights from an industrial case study in technical product development. *Proceedings of the Design Society: DESIGN Conference*, *1*, 757–766.

10.1017/dsd.2020.15

Uhlemann, T.H., Lehmann, C., Steinhilper, R. (2017). The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0. *Procedia cirp* (Vol. 61, pp. 335–340). Elsevier B.V. 10.1016/j.procir.2016.11.152

Weber, C.M., & Yang, J. (2014). Organizational learning and capital productivity in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, *27*(3), 316–326.

10.1109/TSM.2014.2333035

Winters, P.R. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science,*, *6*(3).

World Semiconductor Trade Statistics (WSTS) (2022). *WSTS news release March 2022* (Tech. Rep.). Retrieved from https://www.wsts.org/76/Recent-News-Release

Zhu, L., Johnsson, C., Varisco, M., Schiraldi, M.M. (2018). Key performance indicators for manufacturing operations management – gap analysis between process industrial needs and ISO 22400 standard. *Procedia Manufacturing*, *25*, 82–88. Retrieved from https://www.sciencedirect.com/science/article/pii/S2351978918305791

https://doi.org/10.1016/j.promfg.2018.06.060

Appendix A: Hardware selection

Selection criteria for RTLS is a very important step in the implementation phase (Gladysz & Santarek, 2017; Toro et al., 2021). Gladysz and Santarek (2017) describe wireless technologies commonly used in manufacturing environments are: RFID, Wi-Fi, Bluetooth Low Energy (BLE), Ultra-Wide-Band (UWB), and vision. Subsequently, four main criteria for selecting RTLS technology are drafted in their book on Implementing Industry 4.0 (Toro et al., 2021). These criteria are positioning accuracy, power consumption, cost, and ability to use existing wireless infrastructure. More extensively, Gladysz and Santarek (2017) developed a set of criteria for RTLS selection. Due to the wide range of available technologies they try to answer the question: how to choose the best system for the purpose of a specific case? The main goal of this work was to present and verify a methodology for RTLS selection in industrial environments, because they found a research gap in this area. The criteria were established using a Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). In total, three types of criteria can be distinguished: financial, implementation, and technical. All criteria and their interrelations are presented in Figure 1. The methodology is focused on selecting the right

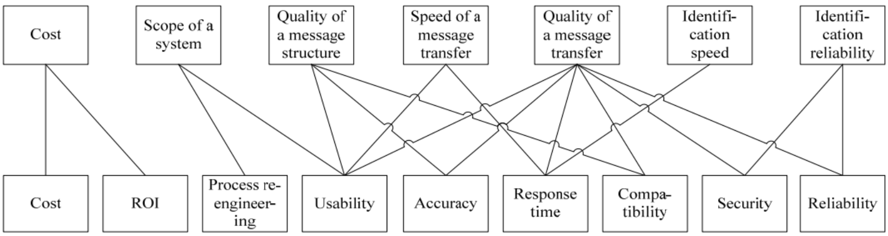


Fig. 1: Sets of RTLS selection criteria and their relation (Gladysz & Santarek, 2017))

technology in an early-stage of RTLS implementation. Prior to this, the question if RTLS is needed and how it contributes to the strategic advantage of the company should be answered first.

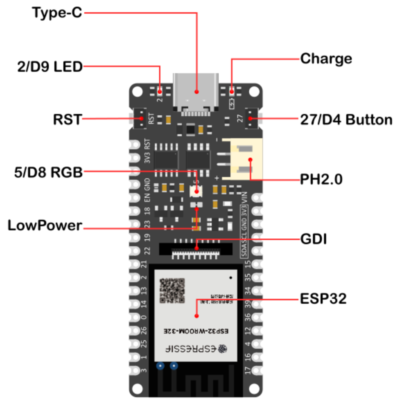
Taking into account the above-mentioned design criteria it was decided to use Bluetooth Low energy tags and anchors as hardware components. Figure 2 presents schematics and more specifications of both tags and anchors. The motivation behind this choice was the following:

- Cost: BLE tags and anchors are relatively cheap due to their popularity in short range communication devices. One requirement was that they should be water proof, because wafer boxes are being washed every now and then.
- Existing infrastructure: Although passive RFID tags are probably the most easy to integrate in existing infrastructue, BLE tags are small and its battery last for around 5 years. Regarding anchors, BLE anchors can be powered by Power Over Ethernet (POE) or USB. This way of powering might favour

UWB as suitable RTLS technology, but re-charging batteries now and then is not desired in this case.
- Accuracy: currently UWB has probably the best accuracy on the market (+-0.1m) depending on interferrence of surrounding objects. Using BLE, this will probably be in the range of +- 1m. Nonetheless, this is considered sufficiently enough for this work.
- Power consumption: BLE has a very low power consumption level

Appendix B: Hardware configuration

(a) Tag



(b) Anchor

Fig. 2: a) Teltonika Bluetooth Low Energy beacon controlled by a ST Microelectronics BlueNRG-2 microcontroller. Range up to 80m and weight of 18 gr. Dimensions 56.6mm x 38mm x 13mm[4]. Casing according to IP67 standard. **b)** FireBeetle 2 ESP32-E. Based on a ESP-WROOM-32E main controller board powered by USB-C. 2.4GHz Wifi and BLE module.[5]

Wafers are transported in wafer transportation boxes. Each box can carry up to 25 3-inch wafers. Figures 3 and 4 contain the box in a closed and open state.

Subsequently tags are attached on the lower back side of a wafer box using 3M double sided circle shaped tape. Tape was preferred over mounting, because of particle generation. After discussion with the shift leaders it turned out that the backside was the only option for beacon placement, since boxes are stacked: excluding the top side. Labels are put on the front and operators are taught to grab the boxes by the long sides, so this leaves us with the back.

Before the complete experiment is installed, a ground truth is established to get a feeling for the accuracy and sensitivity of the selected hardware. First the behavior of Bluetooth signals should be understood. Anchors collect the

Fig. 3: 3-inch wafer box closed (side view)

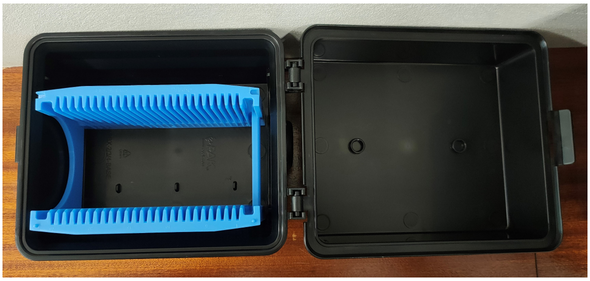


Fig. 4: 3-inch wafer box open (top view)

Received Signal Strength Indication (RSSI) values of beacons. The RSSI value resembles the power of a received radio signal (measured in dBm). A higher RSSI value, represents a higher the signal strength.

Equation (1) presents the theoretical background behind the RSSI value

$$RSSI = -10nlog_{10}(\frac{d}{d_0}) + A_0 \tag{1}$$

where d is the distance between the beacon and the anchor. A_0 reflects a referenced RSSi value at distance $d0$ (in meters). Usually d_0 is set equal to 1.0, such that A_0 becomes the signal strength at 1.0 meter. n is the signal propagation exponent, which is a constant that differs from environment to environment. This formula is derided from Friss' simple transmission formula (Friis, 1946). Rewriting Equation (1) in to Equation (2)

$$d = d_0(10^{\frac{A_0 - RSSI}{10n}}) \tag{2}$$

provides the distance based on the RSSI value.

The test set-up for establishing a ground truth is presented in Figure 5. One anchor is placed on the left side of a table. Two beacons were placed on the table. One beacon at 10cm distance and one at 100cm distance from the anchor. The tests were made in an office space where the environment conditions changed during experiment (people walking, doors opening and closing etc.).

Two calibration experiments were conducted each lasting for 96 hours (4 days). The experiment was conducted twice with different anchors and beacons. The first experiment used anchor 207 and beacons 242 and 257 at distance 10cm and 100cm respectively. The resulting RSSI values are presented in Figure 6 and 7.

The second experiment used anchor 85 and beacons 257 and 242 at distance 10cm and 100cm respectively. The resulting RSSI values are presented in Figure 8 and 9.

Table 1 presents the mean and standard deviation of both experiments as well as the theoretical distance when these mean RSSI values are plugged into

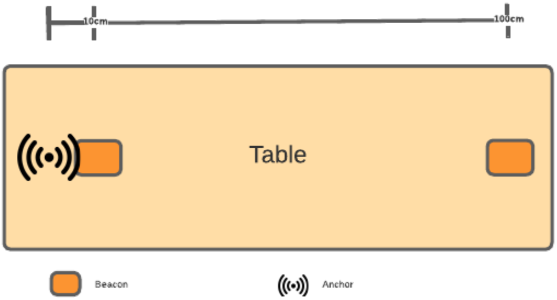


Fig. 5: Calibration set-up. 1 anchor, 1 box at 10cm, and 1 box at 100 cm

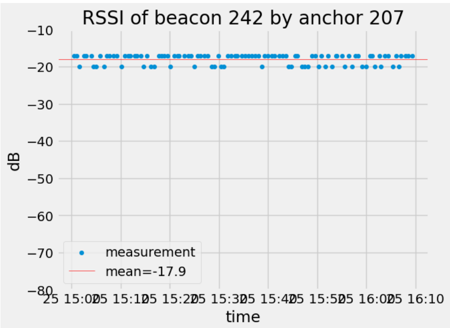


Fig. 6: RSSI of beacon 242. Distance = 10cm. Std. (σ) = 1.387

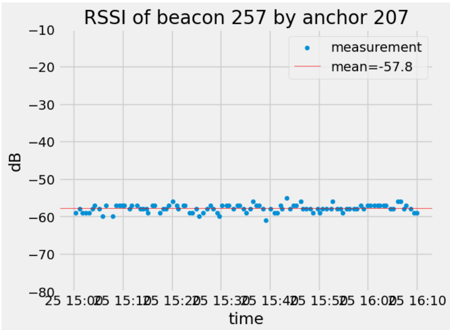


Fig. 7: RSSI of beacon 257. Distance = 100cm. Std. (σ) = 1.025

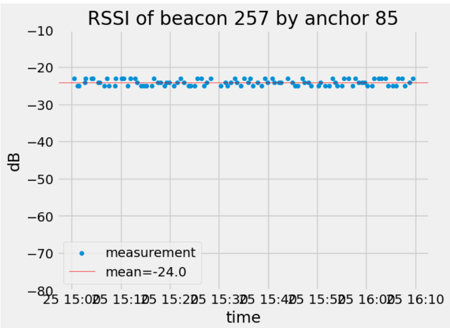


Fig. 8: RSSI of beacon 257. Distance = 10cm. Std. (σ) = 0.843

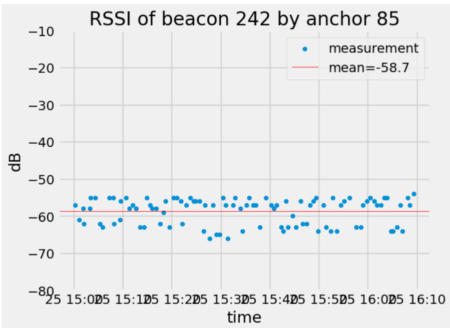


Fig. 9: RSSI of beacon 242. Distance = 100cm. Std. (σ) = 3.513

Equation (2). n was set equal to 2 and A_0 equal to -58 dBm (which was the average of earlier experiments).

Table 1: Results calibration experiment

Experiment	beacon distance (m)	μ_{RSSI}	σ_{RSSI}	μ_d (m)	$\pm sigma$ (m)	mean error (m)
1	0.1	-17.9	1.39	0.010	0.012, 0.008	0.090
	1	-57.8	1.03	0.978	1.100, 0.868	0.022
2	0.1	-24.0	0.84	0.020	0.022, 0.018	0.080
	1	-58.7	3.51	1.084	1.624, 0.724	0.084

Overall the mean errors are all $< 10cm$. For the measurements at 100cm distance this is acceptable, but for the 10cm measurements this is relatively a big error. A possible explanation is the environmental noise. It is therefore advised to make use of a noise filter to improve the accuracy.