DOKTORI (PhD) ÉRTEKEZÉS

Ruppert Tamás

Pannon Egyetem
2020

Az értekezés doktori (PhD) fokozat elnyerése érdekében készült a Pannon Egyetem Vegyészmérnöki- és Anyagtudományok Doktori Iskolája keretében

Bio-, környezet- és vegyészmérnöki tudományok tudományágban

Írta: Ruppert Tamás

Témavezető: Dr. Abonyi János

Elfogadásra javaslom (igen / nem) ....
(témavezető)

Az értekezést bírálóként elfogadásra javaslom:

Bíráló neve: Dr. Bacsárdi László igen / nem ....
(bíráló)

Bíráló neve: Dr. Pfeiffer András igen / nem ....
(bíráló)

A jelölt az értekezés nyilvános vitáján .... %-ot ért el.

Veszprém, ...
(a Bíráló Bizottság elnöke)

A doktori (PhD) oklevél minősítése ....

Veszprém, ...
(az EDHT elnöke)

Pannon Egyetem

Doktori (PhD) Értekezés

Új eszköztár az operátorok munkáját támogató Ipar 4.0 megoldások fejlesztésére

DOI:10.18136/PE.2020.741

Szerző:
Ruppert Tamás

Konzulens:
Prof. Dr. habil. Abonyi János

Értekezés doktori (PhD) fokozat elnyerése érdekében
*a **Pannon Egyetem***

Vegyészmérnöki- és Anyagtudományok
Doktori Iskolájához tartozóan

Folyamatmérnöki Intézeti Tanszék

Pannon Egyetem
2020

University of Pannonia

Doctoral (PhD)Thesis

Industry 4.0 based solutions for operator efficiency improvement

Author:
Tamás Ruppert

Supervisor:
Prof. Dr. habil. János Abonyi

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

in the

Doctoral School in Chemical Engineering and Material Sciences
of University of Pannonia

Department of Process Engineering

University of Pannonia
2020

"Once each discipline is supported by developments in the others, we may begin to understand the ultimate laws of nature and to formulate our human estimate of God's Equation. When the final equation is constructed, we should be able to use it to solve the wonderful riddle of creation. And perhaps that's why God sent us here in the first place."

Amir D. Aczel

PANNON EGYETEM

Kivonat

Mérnöki Kar
Folyamatmérnöki Intézeti Tanszék

Philosophiæ Doctor

Új eszköztár az operátorok munkáját támogató Ipar 4.0 megoldások fejlesztésére

írta: Ruppert Tamás

A kutatás célkitűzése olyan új algoritmusok és nyílt forráskódú eszközök fejlesztése, amelyek felhasználják a különböző monitoring, szabályozó, optimalizációs, ütemezési, kockázati és termék-életciklus adatokat. Az Operátor 4.0 paradigma elsődleges tényezője a szenzor és aktuátor technológiák és kommunikációs megoldások integrálása. A technológiákat bemutatásra kerülnek egy átfogó áttekintés keretében és a jövő munkahelye is felvezetésre kerül, amely az intelligens tér koncepcióján alapul. A valósidejű operátor támogatás és hatékonyság monitoring rendszereknek rendkívül pontos operátori tevékenység információkon kell alapulniuk. A probléma a több száz alaptevékenységi idő: ezek becslése kritikus, köszönhetően a termékek komplexitásának és a terméktípus nagy választékának. Ennek feloldására egy szoftver-szenzor alapú tevékenységidő és hatékonyság mérő rendszert lett kidolgozva.

Az átállási veszteségek jelentősége egyre szignifikánsabb a termelésben, hála a nagy termék-varianciának és az "éppen-időben" (just in time) termelési követelményeknek. Olyan adatvezérelt gyökérok-keresés került kidolgozásra, amelynek segítségével csökkenthetők ezek a veszteségek. Végül, a teljes gyártási folyamat lefedése érdekében gyártósorok irányítása került megvizsgálásra. A ciklusidő-vezérlés és a gyártási szekvencia veszteségeket okozhat, a nem-optimális sorkiegyenlítés miatt. Egy olyan modell-prediktív, vezérlésalapú algoritmust lett kifejlesztve, amelynek segítségével növelhető a gyártósor hatékonysága. Az operátori munka bizonytalanságát fuzzy alapú modellel lett közelítve.

UNIVERSITY OF PANNONIA

Abstract

Faculty of Engineering
Department of Process Engineering

Doctor of Philosophy

Industry 4.0 based solutions for operator efficiency improvement

by Tamás RUPPERT

The goal of the research is the development of new algorithms and open source tools to utilize the data collected by inter-networking systems in monitoring, control, optimization, scheduling, risk management, and product lifecycle management. The primary enabling factor of the resultant Operator 4.0 paradigm is the integration of advanced sensor and actuator technologies and communications solutions. An extensive overview of these technologies are provided and highlights that the design of future workplaces should be based on the concept of intelligent space. Realtime operator support and performance monitoring require accurate information on the activities of operators. The problem with tracing hundreds of activity times is critical due to the enormous variability and complexity of products. A software-sensor-based activity-time and performance measurement system are proposed to handle this problem.

The losses associated with changeovers are getting more significant in manufacturing due to the high variance of products and requirements for just in time production. A method for the reduction of these losses is introduced based on data-driven root cause analysis and performance management. Finally, to handle the entire manufacturing process, the controlling of assembly conveyor lines is studied. The control of cycle time and the sequencing of production can mitigate the losses due to non-optimal line balancing in the case of open-station production where the operators can work ahead of schedule and try to reduce their backlog. A cycle time control algorithm is proposed that can improve the efficiency of assembly lines. A fuzzy-model-based solution has been developed to handle the uncertainty of activity times.

PANNONISCHE UNIVERSITÄT

Auszug

Fakultät für Ingenieurwissenschaften
Abteilung für Verfahrenstechnik

Doktor der Philosophie

Industrie 4.0-basierte Lösungen zur Verbesserung der Bedienereffizienz

von Tamás Ruppert

Ziel der Forschung ist die Entwicklung neuer Algorithmen und Open-Source-Tools, um die von vernetzten Systemen gesammelten Daten für die Überwachung, Steuerung, Optimierung, Planung, das Risikomanagement. Der wichtigste Faktor für das resultierende Operator 4.0-Paradigma ist die Integration fortschrittlicher Sensor- und Aktortechnologien und Kommunikationslösungen. Es wird ein umfassender Überblick über diese Technologien gegeben und hervorgehoben, dass die Gestaltung zukünftiger Arbeitsplätze auf dem Konzept des intelligenten Raums basieren sollte. Echtzeit-Bedienerunterstützung und Leistungsüberwachung erfordern genaue Informationen über die Aktivitäten der Bediener. Das Problem der Rückverfolgung von Hunderten von Aktivitätszeiten ist aufgrund der enormen Variabilität und Komplexität der Produkte kritisch. Zur Bewältigung dieses Problems wurde ein software-sensorbasiertes Aktivitätszeit- und Leistungsmesssystem entwickelt.

Die mit den Umstellungen verbundenen Verluste werden in der Fertigung aufgrund der hohen Variabilität der Produkte und der Anforderungen an die Just-in-Time-Produktion immer bedeutender. Es wurde eine Methode zur Reduzierung dieser Verluste entwickelt, die auf einer datengesteuerten Ursachenanalyse basiert. Schließlich wurde zur Abwicklung des gesamten Fertigungsprozesses die Steuerung von Montagebändern untersucht. Die Steuerung der Zykluszeit und die Sequenzierung der Produktion kann Verluste aufgrund nicht optimaler Linienbalancierung verursachen. Es wird ein Algorithmus zur Steuerung der Zykluszeit vorgeschlagen, womit man die Effizienz der Montagelinien verbessern kann. Es wurde eine auf einem Fuzzy-Modell basierende Lösung entwickelt, um die Unsicherheit der Aktivitätszeiten zu bewältigen.

Acknowledgements

First I would like to say thank you to my supervisor, Prof. Dr. habil. Janos Abonyi! You gave me the support and encouragement I needed and without your guidance and feedback, I would not be here. Thank you for always giving me a second chance and believing in me! You are the best, and it is an honor to explore with you! Thank you!

My thanks also go out to the support I received from the collaborative work I undertook with colleagues of the Sunstone RTLS Ltd. I would also like to say many thanks to my former colleagues in the Department of Process Engineering, they helped me a lot during my Ph.D. studies.

Finally, thank you Rita for all your true kindness. You have tolerated me and gave me strength during all these years.

Szüleimnek

Contents

Chapter 1

Introduction

Industry 4.0 is a strategic approach to design optimal production flows by integrating flexible- and agile manufacturing systems (FMS and AMS) [1] with the Industrial Internet of Things (IIoT) technology enabling the communication between people [2], products, and complex systems [3]. Human resources are still utilized in many manufacturing systems, so the development should focus on the performance of the operators.

As these technologies revolutionize industrial production, the high-tech strategy of the German government launched to promote the computerization of manufacturing was named as the fourth industrial revolution (Industry 4.0). China developed its own initiative. Made-in-China 2025 is a strategic plan announced in 2015 to increase competitiveness in cutting-edge industries including the manufacturing sector [4, 5, 6]. The approach of China is also based on the most modern IT technologies [7] that is not only used to improve the efficiency of the production but also to share manufacturing capacity and support cooperation [8]. The US has introduced "reindustrialization" policies to reinvigorate its manufacturing industry. By releasing the "New Robot Strategy," Japan attempts to accelerate development of cooperative robots and unmanned plants to revolutionize the robot industry, cope with the aggravation of Japanese social and economic issues, and enhance the international competitiveness. The "New Industrial France" the "high-value manufacturing" strategy of UK, and the "advanced innovators' strategy" of South Korea have similar CPS based focus points [9]. The common goal of these developments is to integrate the supply chain. Industry 4.0 and additive manufacturing, when combined, can help enable the creation of products that are first-to-market and fully customized. Thanks to the benefits of additive manufacturing not only the consumer can find more customized products and services, but also the manufacturer has a chance to create more efficient and scalable production flow [10]. All in all, these novel manufacturing technologies appear to herald a future in which value chains are shorter, more collaborative, and offer significant sustainability benefits.

Organizations should be prepared for the introduction of Industry 4.0 based complex production systems. Recently developed maturity or readiness models are mainly technology focused [11, 12] and assess the Industry 4.0 maturity of industrial enterprises in the domain of discrete manufacturing [13]. Thanks to the fast and flexible communications between CPSs, smart sensors and actuators, real-time and self-controlled operations can be realized [7, 2]. The new smart IoT (Internet of Things) devices have the potential to design mobile machines that replace human minds [14]. Researchers at Oxford University estimated that approximately 47% of all US employment will be at a high risk of computerization by the early 2030s [15]. A survey conducted by PricewaterhouseCoopers (PwC) found that 37% of employees were worried about the possibility of redundancy due to automation [16, 15].

Although state of the art in the area of Industry 4.0 has been reviewed recently [4], systematic literature reviews are frequently published [17, 18, 19], there is a need to study that the fourth industrial revolution will not entirely replace operators, instead sensors, smart devices, mobile IoT assets, and technologies will be used to design systems for operator support.

Although the increase in the degree of automation reduces costs and improves productivity [20], human operators are still essential elements of manufacturing systems [21, 22].

The fast development of smart sensors and wearable devices has provided the opportunity to develop intelligent operator workspaces. The resultant Human-Cyber-Physical Systems (H-CPS) integrate the operators into flexible and multipurpose manufacturing processes. The primary enabling factor of the resultant Operator 4.0 paradigm is the integration of advanced sensor and actuator technologies and communications solutions. This work provides an extensive overview of these technologies and highlights that the design of future workplaces should be based on the concept of intelligent space.

This thesis considers four main problems of flexible manufacturing systems (Figure 1.1). Operators need all support in case of rapid production [23]. The fourth industrial revolution considers the accessories for workers. In the next Chapter (Chapter 2), I will make an overview of the Operator 4.0 concept, which can provide all information to the operator with the newest IIoT technologies. The right picture of the daily work is a crucial element of the modular production [24]. The activity times are stochastic and many types of distribution in case of modular production.

Real-time operator support and performance monitoring require accurate information on the activities of operators. The problem with tracing hundreds of activity times is critical due to the enormous variability and complexity of products. To handle this problem a software-sensor-based activity-time and performance measurement system is proposed. The proposed model-based performance monitoring system tracks the recursively estimated parameters of the activity-time estimation model. I will show the challenges of operator performance monitoring in Chapter 3.

The losses associated with changeovers are getting more significant in manufacturing due to the high variance of products and requirements for just in time production. The many types of products [25] are a big challenge and opportunity for changeover optimization [26]. The operator is a crucial element of the process even in case of fully automated manufacturing machines too. The changeovers are manually (partly or fully). I introduced a method for the reduction of these losses based on data-driven root cause analysis and performance management. The method is based on models that estimate the product- and operator- dependent changeover times by survival analysis. The root causes of the losses are identified by significance tests the utilized Cox regression models. The resulted models can be used to design a performance management system that takes into account the stochastic nature of the work of the operators. In Chapter 4, I will show the developed algorithm and targeting model.

The fourth analyzed issue is the optimal cycle time in case of mixed production [27]. The control of cycle time and the sequencing of production can mitigate the losses due to non-optimal line balancing in the case of open-station production where the operators can work ahead of schedule and try to reduce their backlog. I will provide a cycle time control algorithm that can improve the efficiency of assembly lines in such situations based on a specially mixed sequencing strategy in Chapter

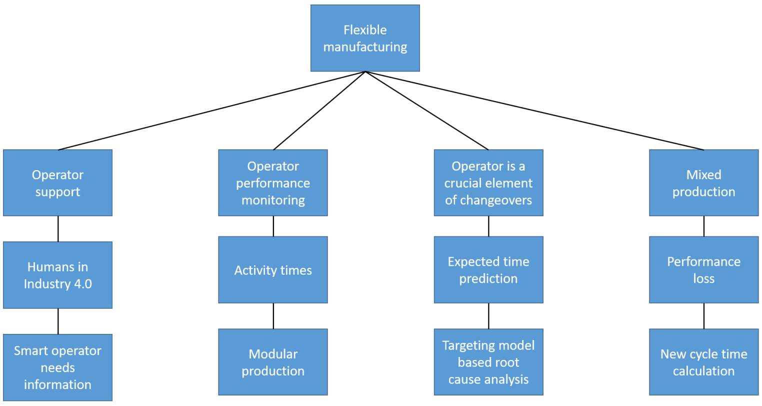

FIGURE 1.1: The problems of flexible manufacturing are divided into three main topics. The operator support considers the technological solutions for human resources, while the changeovers and mixed production are described the manufacturing problems.

5. To handle the uncertainty of activity times, a fuzzy model-based solution has been developed. As the production process is modular, the fuzzy sets represent the uncertainty of the elementary activity times related to the processing of the modules. The optimistic and pessimistic estimates of the completion of activity times extracted from the fuzzy model are incorporated into a model predictive control algorithm to ensure the constrained optimization of the cycle time.

To handle the uncertainty of the operator's activities, I developed three different types of time models (Figure 1.2). The first model is the module content-based activity times analyses, where the base activities and the module content with the built-in components are defined. The activity time analysis is the pillar of production planning and process optimization. The second model is the changeover time prediction based on the log data. In that case, I developed a survival model to identify the time probability. In the third model, I defined a fuzzy-set to handle the assembly time uncertainty at the open station based conveyor assembly line. To solve the line balancing and production scheduling problem, I defined optimistic and pessimistic estimates of the activity time.

Figure 1.2 shows the concept of this thesis. The three pillars are defined, where the first step is to explore the main activities and identify the connection between the parts of a complex system. The next step is the time measurement, where the data from the shop floor is used for the prediction. Finally, to increase the process improvement, the real-time assembly line control-based on the activities are proposed.

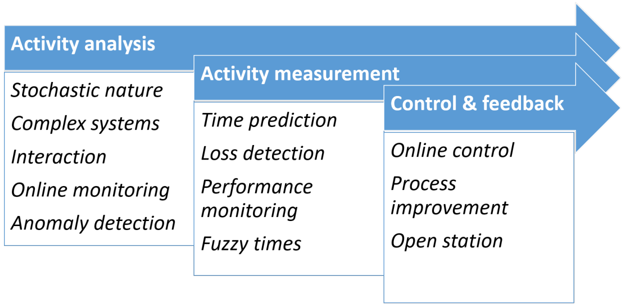

FIGURE 1.2: The thesis defines three pillars. Explore the main activities is the first step of the proposed system. If the activities are defined, then the next step is the time measurement. Finally, the real-time assembly line control based on the activities are proposed to increase the process improvement.

The applicability of the proposed method is demonstrated based on a wire-harness manufacturing process with a paced conveyor, but the proposed algorithm can handle continuous conveyors as well. The results confirm that the application of the proposed algorithm is widely applicable in cases where a production line of a supply chain is not well balanced and the activity times are uncertain.

The human role in Industry 4.0 is a complex issue. The concept of Operator 4.0 is described in the next Chapter. The intelligent space is also proposed, based on the new IIoT technologies to provide real-time information for operators.

Chapter 2

Operator in Industry 4.0

The human resources in a manufacturing area are continuously a crucial critical factor, but the theory of the 4th industrial revolution is impacting there. In this concept, the optimization is realized by Cyber-Physical-Systems (CPS) developed to utilize information related to product models, simulators and process planning data (see Figure 2.1). With the extensive inter-system communication of the elements of CPSs and smart sensors and actuators [2] real-time optimal and self-controlled operation can be realized [7].

Industry 4.0 (especially IoT devices and CPS) allows new types of interactions between operators and machines [28]. These interactions will generate a new intelligent workforce and have significant effects on the nature of work. The integration of workers into an Industry 4.0 system consisting of different skills, educational

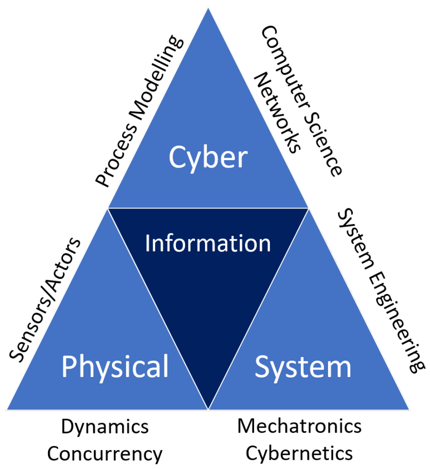

Figure 2.1: Cyber-Physical-Systems (CPS) are based on the connection of the information related to production systems and process models.

levels and cultural backgrounds is a significant challenge. The new concept of Operator 4.0 was created for the integrated analysis of these challenges. The concept of Operator 4.0 is based on the so-called Human-Cyber-Physical Systems (H-CPS) designed to facilitate cooperation between humans and machines [29].

This chapter focuses on the elements of this infrastructure and proposes an intelligent space-based design methodology for the design of Operator 4.0 solutions. According to this goal the development and application of advanced internet-of-things technologies with regard to smart sensing technologies, IoT architectures, services and applications will be discussed by following the types of the Operator 4.0 solutions proposed by Romero et al. [30, 29].

The chapter is comprised of the following structure. The elements of Operator 4.0 solutions are presented and a novel design methodology based on the concept of intelligent space proposed in Section 2.1. The required infrastructural background is presented in the remaining sections. IoT solution for tracking operator activities is introduced in Section 2.2. Conclusions and recommendations based on the review proposed in Section 2.3.

2.1 Framework of Operator 4.0 Solutions

The concepts of Operator 4.0, cyber-physical systems and intelligent space are introduced and connections between these methodologies discussed in this section.

2.1.1 The Operator 4.0 Concept and Human-Cyber-Physical Systems

Operator 4.0 typology depicts how the technologies of the fourth industrial revolution will assist the work of operators [29]. Operator 1.0 is defined as humans conducting manual work. The Operator 2.0 generation represents a human entity whose job is supported by tools, e.g., by computer numerical control (CNC) of machine tools. In the third generation, the humans are involved in cooperative work with robots and computer tools, also known as human-robot collaboration.

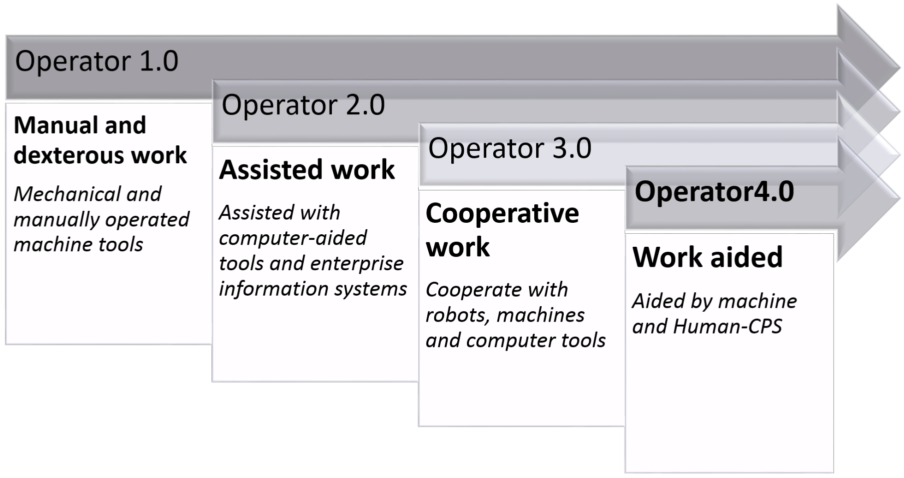

FIGURE 2.2: (R)evolution of the tasks of operators in manufacturing systems.

This human-robot collaboration in the industrial environment is a fascinating field with a specific focus on physical and cognitive interaction [31]. However, the new set of solutions is based on even more intensive cooperation between operators and production systems. This new Operator 4.0 concept represents the future of workplaces [29] (see Figure 2.2).

The main elements of the Operator 4.0 methodology are explained in Table 2.1. Analytical Operator-type solutions utilize Big Data Analytics to collect, organize and analyze large data sets [30]. Augmented reality (AR) can be considered as a critical enabling technology for improving the transfer of information from the digital to the physical world of the smart operator. The Collaborative Operator works together with collaborative robots (CoBots). Healthy Operator solutions measure and store exercise activity, stress, heart rate and other health-related metrics as well as GPS location and other personal data. Smarter Operators interact with machines, computers, databases and other information systems as well as receive useful information to support their work. Social Operators use mobile and social collaborative methods to connect to smart factory resources. Super-Strength Operators increase the strength of human operators to be able to conduct manual tasks without effort using wearable exoskeletons, while Virtual Operators interact with the computer mapping of design, assembly or manufacturing environments.

TABLE 2.1: Elements of the Operator 4.0 methodology according to [30, 29].

Type of Operator 4.0	**Description**	**Examples**
Analytical operator	The application of big data analytics in real-time smart manufacturing.	Discovering useful information and predicting relevant events [32, 33].
Augmented operator	AR-based enrichment of the factory environment. AR improves information transfer from the digital to the physical world.	Smartphones or tablets are used as Radio Frequency IDentification (RFID) readers and can become key tools of smart manufacturing [34, 35, 36].
		Spatial AR projectors support automotive manufacturing [37, 38, 39].
Collaborative operator	CoBots are designed to work in direct cooperation with operators to perform repetitive and non-ergonomic tasks.	Rethink-Robotics with Baxter & Sawyer promises low-cost and easy-to-use collaborative robots [40].
Healthy operator	Wearable Trackers are designed to measure activity, stress, heart rate and other health-related metrics as well as GPS location and other personal data.	Apple Watch, Fitbit and Android Wear-based solutions had already been developed [30].
		Military-based applications can predict potentially problematic situations before they arise [30].
Smarter operator	Intelligent Personal Assistant (IPA)-based solutions that utilize artificial intelligence.	Help the operator to interact with machines, computers, databases and other information systems [41].
Social operator	Enterprise Social Networking Services (E-SNS) focus on the use of mobile and social collaborative methods to connect smart operators on the shop-floor with smart factory resources.	The Social Internet of Industrial Things interacts, shares and creates information for the purpose of decision-making support [42].
Super-strength operator	Powered exoskeletons are wearable, lightweight and flexible biomechanical systems.	Powered mechanics to increase the strength of a human operator for effortless manual functions [43].
Virtual operator	Virtual Reality (VR) is an immersive, interactive multimedia and computer-simulated reality that can digitally replicate a design, assembly or manufacturing environment and allow the operator to interact with any presence within.	Provide the user with an environment to explore the outcomes of their decisions without putting themselves or the environment at risk [44].
		The VR–based gait training program provides real-time feedback [45].
		Multi-purpose virtual engineering space [46].

TABLE 2.2: Design principles of Industry 4.0 applied to Operator 4.0 solutions.

Design principle	**Description**	**Application**
System integration	combines subsystems into one system. Vertical integration connects manufacturing systems and technologies [50], horizontal integration connects functions and data across the value chain [1].	Analytical operator
Modularity	is important for the ability of the manufacturing system to adapt to continuous changes [51, 52, 53].	Augmented operator
Interoperability	allows human resources, smart products and smart factories to connect, communicate and operate together [51]. The standardization of data is a critical factor for interoperability because the components have to understand each other.	Collaborative operator
Product personalization	the system has to be adapted to frequent product changes [54].	Smarter operator
Decentralization	is based on the distributive approach, where the system consists of autonomous parts which can act independently [51]. It simplifies the structure of the system which simplifies the planning and coordination of processes and increases the reliability [55].	
Corporate social responsibility	involves environmental and labor regulations.	Social operator
Virtualization	uses a digital twin, i.e., all data from the physical world is presented in a cyber-physical model [56].	Virtual operator

Whit regards to the development of Operator 4.0-based automation systems, attention has to be paid to the design principles of Industry 4.0 solutions, which are decentralization, virtualization, reconfiguration and adaptability [47, 48, 49]. How these principles should be applied during the development process is presented in Table 2.2.

Level	Interpretation of CPS levels	Function
Configuration level	Supervisory control Required actions	Actions to avoid
Cognition level	Decision support	Prioritize and optimize decisions
Cyber level	Adaptive analysis Time-machine snapshots	Self-compare
Data-to-Information Conversion level	Machines Components	Self-aware
Smart connection level	Sensors	Condition monitoring

FIGURE 2.3: Architecture of cyber-physical systems.

The Operator 4.0 concept aims to create Human-Cyber-Physical Production Systems (H-CPPS) that improve the abilities of the operators [30]. The allocation of tasks to machines and operators requires the complex semantic model of the H-CPS. Operator instructions can be programmed into a machine and but handling uncertainty and stochastic nature is difficult. Adaptive systems are suitable to handle these problems with the help of more frequent monitoring and model adaptation functions [57, 58, 59, 60]. Real-time operator support and performance monitoring require accurate information concerning the activities of operators, which means all data related to operator activities should be measured, converted, analyzed, transformed into actionable knowledge and fed back to the operators. Based on this requirement, the operator should be connected from the bottom (connection) to the top (configuration) levels of the cyber-physical systems [61]. To support this goal, an overview concerning the elements of CPS from the perspective of operators is given in Table 2.3 and the levels of CPSs with a description of the functions and tasks are presented in Figure 2.3.

As tasks should be transformed into a form that computers can understand, task analysis is becoming more crucial due to the difficulties of the externalization of the tacit knowledge the operators [62]. Tacit knowledge contains all cognitive skills and technical know-how that is challenging to articulate [63, 64]. Without elicit tacit knowledge, the chance of losing critical information and best practice is very high [65]. Hierarchical task analysis extended with the 'skill, rule and knowledge" framework can capture tacit knowledge [66], which approach has been proven to be useful in manufacturing [67]. Sensor technologies are essential to elicit tacit knowledge, for example, the tacit knowledge of the operator can be captured by a 'sensorized' hand-held belt grinder and a 3D scanner to generate a program of

TABLE 2.3: Levels of cyber-physical systems from the perspective of operators.

Level	Function	Example
Configuration	Self-optimize	Prediction and online feedback with regard to quality issues [75, 76]
	Self-adjust	
	Self-configure	
Cognition	Collaborative diagnostic and decision-making	VR [77, 78, 79]
	Remote visualization for humans	AR [80, 81, 82]
Cyber	Digital twin	Decision-making based on a digital twin [83, 84, 85]
	Model of operator	Worker-movement diagram [86, 87, 88, 89]
		Monte-Carlo simulation of a stochastic process model [90, 91]
Conversion	Smart analytics	Online performance monitoring based on sensor fusion [92, 93]
	Degradation and performance prediction	
Connection	Sensor network	Wearable tracker [94, 95]
		Indoor Positioning System [96, 97, 98, 99, 100]

a robot that can replace the operator [68]. The modelling of the physical reality and realising it in the CPS are critical tasks [69, 70, 71, 72].

These examples illustrate that Operator 4.0 solutions should be based on contextual task analysis which requires precise chronological time-synchronization of the operator actions, sensory data and psycho-physiological signals to infer the cognitive states [73] and emotions [74] associated with the decisions and operator actions.

Sensors and feedback technologies of interactive intelligent space can be used not only for improving the abilities of the operators but also for the extraction of their tacit knowledge. In the following section, these technologies will be detailed.

2.1.2 The Operator 4.0 Concept and Intelligent Space

In the previous section, the key functions of Operator 4.0 solutions were shown to be related to the monitoring and support of operator activities. The most significant trend is related to the development of human-machine interfaces that embrace interaction in a set of novel ways [101]. As the operator performs tasks, real-time information is provided about the production system and real-time support is received from it. Interactive human-machine systems had already been introduced in the Hashimoto Laboratory at the of University of Tokyo [102] where an Intelligent Space (iSpace) system has been designed for the virtual and physical support of people and mobile robots [103]. Intelligent interaction space supports the operators to complete their work with high efficiency, high success rate, and low burden [104]. The iSpace framework is shown in Figure 2.4.

The events within iSpace are continuously monitored by Distributed Intelligent Network Devices (DINDs) consisting of various networked sensors, e.g., indoor positioning systems and cameras for localization. DINDs interpret events in the physical space and provide services (feedback) to operators using physical devices, e.g., microphones, displays, etc. According to the horizontal integration concept, the proposed iSpace is also connected to suppliers and customers. This concept highlights that iSpace should relay on CloudThings architecture that integrates IoT and Cloud Computing [105], as cloud computing enables a convenient, on demand, and scalable network access to a shared pool of configurable computing resources.

Resources, users, and tasks are the three core elements of intelligent interaction space (see Figure 2.5). The user-resource-task model supports the design of interaction among these components [104] which interactions should handle how resources trigger the tasks and how the tasks are assigned to the operators based on their availability, performance, and competence.

Intelligent space should respond to requests from people, so the activities of the operators must be identified by cameras, internal positioning systems, or based on voice signals, and these multi-sensory data should be processed by artificial intelligence and machine learning solutions [103]. The acquired information is transmitted via a wireless network and processed by dedicated computers, so any event involving or change in the monitored parameters inside the space is carefully analyzed and processed [106].

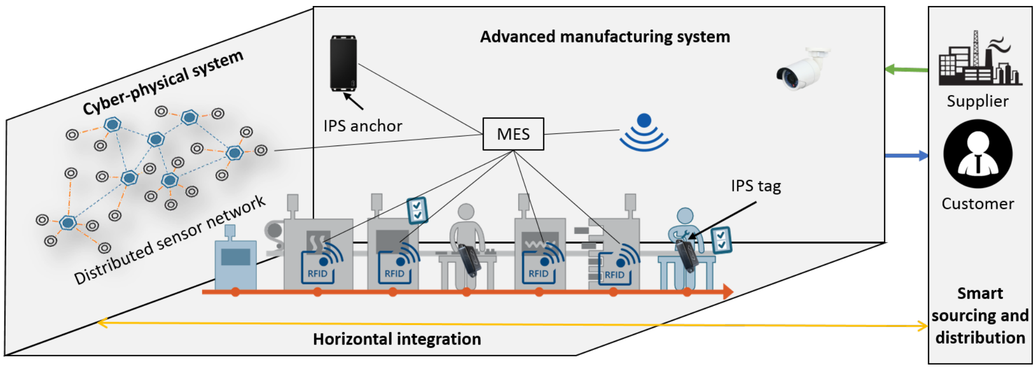

FIGURE 2.4: iSpace based integrated sensor signals can be used to monitor the work of the operators, extract their tacit knowledge, synchronize activities, and provide contextualized information.

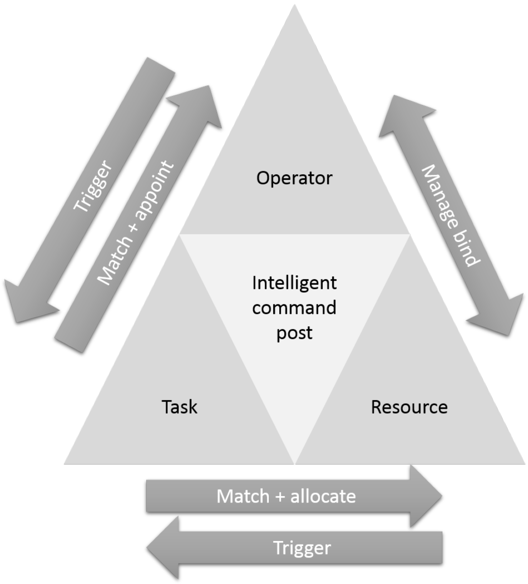

FIGURE 2.5: The design of connections between resources, users, and tasks is the key of the design of intelligent interaction space.

This section highlighted that the development of H-CPSs requires an appropriate design concept. According to the concept of intelligent space the architecture must be modular, scalable and integrated, which results in low installation and maintenance costs and easy configuration [107].

2.2 IoT-based Solutions to Support Operator Activities

From the viewpoint of operators, connection and conversion are the most critical levels of cyber-physical systems as these two levels are responsible for interaction. As smart sensors are key components of solutions for cyber-physical production systems (CPPS) [2], it is necessary to overview what kind of tools are available for monitoring the activity of the operators.

Usually, operator activity is monitored by RFID-based object tracking [108]. This technology can collect real-time data about the activities of workers (operators) and machines, as well as movements of materials [109] and workpieces [110, 111]. Multi-agent supported RFID systems realize location-sensing systems [112] and intelligent-guided view systems [113]. RFID systems for human-activity monitoring provide an excellent opportunity to observe the work of the operators [114].

With the help of these devices, the whole production process as well as production and waiting times have become measurable online. Based on this information, shop floor control (SFC) and optimization can also be realized. When the RFID readers are placed such that the duration of the tasks can be estimated, how the production line is balanced in addition to the effect of product changes can be evaluated, and real-time data for OEE (Overall Equipment Effectiveness) calculations provided [115].

The tracking of production can be significantly improved by indoor positioning system (IPS) utilized for localizing the positions of the products and operators [96]. The applications of IPS and its potential benefits in terms of process development are complied in Table 2.4.

Context-aware systems require unobtrusive sensors to track each step of the performed task [116]. As wearable sensors are becoming more common, their utilization is also becoming more attractive [117]. However, hand motion-based activity recognition is still challenging [118] and requires the application of advanced machine learning algorithms [119]. Tracking operator activity is a challenging and highly infrastructure-demanding task which should utilize information stream fusion approaches to improve the robustness of the algorithms [120]. How all these smart sensor-based IoT technologies can be used to design Operator 4.0-type solutions is compiled in Table 2.5.

The operators not only have to provide real-time information about their actions but at the same time require real-time support in their work. Industrial wearable [94] and communication [139] solutions help to handle this challenge. The previous paragraph showed what kind of techniques exist to collect information from the operator. In this section, potentially applicable feedback technologies will be introduced which are related to the configuration level of cyber-physical systems [61].

In the early applications production activities required to complete orders were scheduled and managed by shop floor control systems (SFCS). In [140] a hierarchical SFCS (shop, workstation, equipment) was adopted. In [141] a vision-based human-computer interaction system was introduced that interacts with the operator and provides feedback. Complex hardware was installed in intelligent environments, equipped with a steerable projector and spatial sound system, to position the character within the environment [142].

A potential grouping of feedback technologies is the following: fix-mounted devices (e.g., LED TVs), mobile devices (e.g., tablets, smartphones) and wearable devices (e.g., smart glasses). Intuitive displays can reduce the cost of operator intervention as the performance of the operator is improved by the auditory and visual understanding [143]. Visual collaboration systems can provide appropriate instructions for each step of the assembly task [144]. All groups are used correctly and efficiently, but the novelty of wearable devices compared to the 'simple' mobile devices is the total freedom of movement and free use of limbs [145]. So far some of these only provide a human-machine interface (HMI) and need a (mobile) computer (e.g., a smartphone) to operate, but the tendency is that every device will work separately and can cooperate with other devices through some communication solutions (e.g., LAN/WiFi, Bluetooth). Headsets, VR helmets, smart gloves and smart clothes are examples of types of devices presented in Table 2.6. The importance of this area is shown in the statistical increase in the numbers of sales. So far these kinds of solutions have resulted in approximately $5.8 billion in business [146].

The connections between the categories of Operator 4.0 solutions and potential feedback technologies are shown in Table 2.6. Which feedback opportunity is expedient is defined by the task in question. For example, in the case of the

Table 2.4: Applications of indoor positioning systems in production management.

Application area	**Description**	**Examples**
Performance monitoring	Measure effects of process development and business process reengineering (BPR).	Analyse moving- and staying-time of operators [121].
Movement analysis	Spaghetti diagram of operator movement to reduce unnecessary movement and optimise the layout and supply chain.	Reduce the duration of material handling [122]. Reduce the number of unnecessary movements of operators [121]. Support real-time manufacturing execution systems (MES) [123].
Support 5S projects	Track tools and optimise the place of application and storage.	Decrease of stock and scrap. Improve activity times [121].
Digital twin	Direct process the on-line information inside the process-simulation tools. Prove the real-time architecture for the Digital Twin method.	The main elements of the real-time architecture are the 'Digital Twin' and IPS [124].

Table 2.5: Sensors of Operator 4.0 solutions.

Type of Operator 4.0	Type of sensor	Examples
Analytical operator	Infra-red sensors	Discover and predict events [103]
	Olfactory sensors	Electronic nose [125]
Augmented operator Virtual operator	Microphones	Capturing voices and the location of speakers [126]
	Visual sensors	Machine vision systems for quality inspection [127, 128]
		Image processing, e.g., panoramic images [129], create the environment of virtual reality [130]
		Smart camera for probabilistic tracking [131]
Collaborative operator Social operator	Localization sensors	IPS in manufacturing [96] and hybrid locating systems [132]
		Mapping and localization using RFID technology [133] and efficient object localization using passive RFID tags [134, 135]
		Smart and social factories based on the connection between machines, products and humans [136]
Smarter and healthy operator	Wearable sensors	Smart watch with embedded sensors to recognize objects [137]
		The smart glove maps the orientation of the hand and fingers with the help of bend sensors [138]

Super-Strength operator the feedback indicating danger is a critical function. The next step of the design is to select the technology that delivers the information. Danger can be indicated with the help of smart glasses or by a speaker. As soon as the operator hears the warning alarm the danger can be avoided. In the case of smart glasses, the worker can obtain more detailed information about the type and location of risk. The potential applications of these solutions are summarized in the last column of the table.

Some companies have been testing these innovative technologies in manufacturing processes. In every case when these techniques are used, the production process is complex, the quality management is strict, and there is a wide variety of products. The results are impressive because the efficiency improves while the learning time reduces in every observed situation. In the following, some of these solutions will be introduced.

Smart glasses-based augmented reality is used in the manufacturing of high-horsepower wheeled tractors with hundreds of variations by the company AGCO [148]. Presently, 100 pairs of glasses are in use to visualize the next manufacturing step and necessary information for the inspection process. The results in numbers are promising:

- 50% reduction in learning time (in the case of new workers)
- 30% reduction in inspection time (eliminates paperwork and manual upload)

TABLE 2.6: Feedback technologies for Operator 4.0 solutions.

Operator 4.0	**Feedback**	**Technologies**	**Examples**
Analytical operator	Report / Potential danger	Smart glasses, smartphones, tablets and personal displays	Big data-based development of a manufacturing process [147].
Augmented operator	Each possible feedback	Smart glasses	AR for tractor manufacturing [148]. Smart glasses [149, 30].
Collaborative operator	Waiting for interaction / Technical problem	Smart glasses, smartphones, tablets, personal displays, headsets and smartwatches	Collaborative operator workspace [150].
Healthy operator	Need rest	Smart glasses, smartphones, tablets, personal displays and headsets	Measurement of physiological parameters [151, 152]. Security issues [153].
	Change activity		
	Need a medical test		
Smarter operator	Answer to a question	Smart glasses, smartphones, tablets, personal displays and headsets	Chatbot [154] and AI provide support to operators [155].
	Notice about an event		
	Process		
Social operator	Emergency	Smart glasses, smartphones, tablets, personal displays and headsets	Facebook-based product avatar [42] and Social Manufacturing (SocialM) [54].
	Process		
	Manufacturing		
	Technical information		
Super-strength operator	Optimal route / Targeting / Training	Smart glasses, tablets and smartphones	Navigation [156, 157] and targeting [158, 159, 157].
	Force feedback on a hand or whole arm	Smart gloves and special exoskeletons	HaptX [160], VRgluv and ABLE Project [161, 43] are such technologies.
	Danger indicator	Smart glasses and speakers	Safety and risk management (related to exoskeleton technology) [162].
Virtual operator	Collision / Weight / Pressure	Smart clothes / smart gloves	VR technology in prototyping and testing [163]. This kind of technology becomes more efficient with every wearable feedback device (e.g., smart gloves [164]) that use (secondary) human senses directly.

- 25% reduction in production time (in the case of complex assemblies and low volumes)

Similar advantages of smart glasses were reported at DHL which is one of the leading logistics companies in the world [157]. Ten workers who used smart glasses for three weeks managed to distribute 20,000 packages (9,000 orders) leading to a 25% increase in the efficiency of the operators and a reduction in errors of 40%.

Quality and reliability are critical in aerospace manufacturing. Boeing and Model-Based Instructions (MBI) from Iowa State University support the work of the operators. Their first solution was designed to show the instructions for the workers. The installation of the desktop MBI was static and there were numerous situations when the operator could not see them during the assembly process. The tablet MBI used the same instructions as the desktop MBI, but it was mounted on a mobile arm. The tablet AR was the same tablet that provided the tablet MBI solution, but the operator could see the real world on the display of the tablet and the software added virtual elements into the video stream. It was observed that the AR technology yielded the best solutions with regard to first-time quality, speed and worker efficiency out of these three solutions [165, 166].

These benefits are in accordance with what was observed in the introduction of general Industry 4.0 solutions [167]. The examination of 385 published applications shows that the most common benefits of Industry 4.0 are the enhanced efficiency (47%), prevention of errors (33%), reduction of cost (33%), employee support (32%) and minimization of lead time (31%). It is worth noting that the importance of communication (31%), human-machine interfaces (25%) and sensor technology (11%) were also highlighted.

The review concerning examples of applications showed clearly that the Operator 4.0 concept works in practice and the following advantages were observed: (1) elimination of classical paper-based administration, (2) operators can use their arms freely and receive real-time feedback about the manufacturing process, (3) the duration of training of workers decreases, and (4) the efficiency of production increases and the number of errors decreases simultaneously in all cases. In summary, operators will be more efficient in smart workplaces, where new opportunities will be available to safeguard their activities and ensure alertness. Production systems will become safer, more controllable and manageable than ever before. A win-win situation will develop in which humans remain an important element. Operator 4.0 technologies only capable of bringing about these benefits when the manufacturing process is complex and the variety of products is wide. Of course, some advantages can be observed in cases of traditional mass production too, but it is difficult to compensate for the high investment and development costs of these technologies.

2.3 Conclusion of Operator 4.0

This chapter provided an overview of what kind of Industrial Internet of Things-based infrastructure should be developed to improve the efficiency of operators in production systems. By following the Operator 4.0 concept proposed by Romero et al. [30, 29], literature survey demonstrated that smart sensors and wearable devices provide the opportunity to integrate operators into the concept of smart factories.

It was highlighted that integrated workspaces should have modular and integrated architecture and the development should be based on the concepts of human-in-the-loop cyber-physical systems and intelligent space to ensure low installation and maintenance costs.

In this chapter, the architecture and infrastructure of Operator 4.0 technologies were surveyed. Monitoring and data-driven analytics is the key of process development [139, 17]. There are several exciting model- and algorithm-based aspects of these solutions, e.g., big data, sensor fusion and optimization, and machine learning whose review would also be timely as significant added value and reductions in cost can be achieved by the model-based monitoring, control and optimization of the presented production support systems.

In order to analyze the operator in the manufacturing environment, the models of manufacturing are needed. In the next chapter, a multilayer network model for the exploratory analysis of production technologies is proposed. To represent the relationships between products, parts, machines, resources, operators and skills, standardized production and product-relevant data is transformed into a set of bi- and multipartite networks. This representation is beneficial in production flow analysis (PFA) that is used to identify improvement opportunities by grouping similar groups of products, components, and machines.

In the next Chapter, a software sensor method is represented to support activity-time monitoring and fault detection in production lines. The activity-based process line control is shown in Chapter 5, where the model predictive control is developed based on fuzzy activity times. Finally, a survival analyses technique is described in Chapter 4 to improved the changeover times in case of manufacturing systems.

Chapter 3

Software sensor for activity-time monitoring

In the age of digital transformation, human operators are still applied in manufacturing processes. The Operator 4.0 concept aims to create human-cyber-physical production systems (H-CPPS) that improve the abilities of the operators' thanks to the dynamic interaction between humans and production systems [30]. Smart sensors are key components of CPPS solutions [2]. Model-based production control and performance monitoring require accurate information concerning the activity times of the operators. Handling human factors is a challenging problem in terms of both cellular manufacturing [168] and human-robot interaction [169]. Usually, operator activity is monitored by computer vision-based motion detection systems and RFID-based object tracking [108]. Context-aware systems require unobtrusive sensors to track each step of the performed task and present the worker with the information needed at any given moment [116]. As wearable sensors are becoming more common, their utilization is also becoming more attractive [117]. However, hand motion-based activity recognition is still challenging [118] and requires the application of advanced machine learning algorithms [119]. As this brief overview shows as well, the tracking of operator activity is a difficult, highly infrastructure-demanding task which should utilize information stream fusion approaches to improve the robustness of the algorithms [120].

Tracing hundreds of primary activities is critical due to the enormous variability and complexity of products. As every operator performs sequentially a specific set of actions over a period of time, our goal is to develop a sensor system that continuously estimates the time consumption of these elementary activities. I model the time consumptions of these actions by activity time models and compare the estimated activity times to the performance of operators and generate early warnings when their productivity decreases.

For the cost-effective and robust measurement of assembly times, sensors were developed to record the timestamps related to the activity when the components are pushed into the fixtures by operators. As the activities of operators depend on the type and number of the built-in components, the production flow is tracked by an IPS.

To integrate measurements originating from the IPS, a varying number (10–100) of active or passive fixture sensors, and other information sources of the production management system, a multi-sensor data fusion (MSDF) algorithm has been developed. Multiple sensors provide redundancy enabling the robust recursive estimation of the unmeasured primary activity times of the operators. To constrain the model parameters to lie within a reliable region and incorporate important *a priori* knowledge concerning the activity times, the estimated parameters were optimally projected on to a set of linear constraints by quadratic programming [170]. This central estimation enhances the confidence of the nominal model which improves the performance of fault detection based on the reconciliation of the local measurements.

The development of the proposed fault-detection algorithm is motivated by the analysis of an industrial wire harness manufacturing process which is a typical complex modular product manufacturing system [171, 172]. The developed algorithm can be used in the general activity time monitoring where some activity points are measured. To ensure our results are fully reproducible, only openly available information on wire harness manufacturing technologies was utilized during the development of the realistic case study.

This section is structured as follows. The developed IIoT-based sensor system is shown in Section 3.1. The applicability of the proposed activity-time estimation algorithm is demonstrated in Section 3.2. Based on the findings and discussions reported there, conclusions are drawn in Section 3.3.

3.1 Evaulation of activity times with software sensor

In the present section, first the conveyor and the modular production systems are characterized, then the fixture sensors and the indoor positioning system as information sources are described. This is followed by the mathematical formulation of the multi sensor data fusion-based recursive estimation model and finally by the local estimation and monitoring with regard to the activity times of operators.

3.1.1 Problem definition—evaluation of activity times on the paced conveyor

The crucial part of the studied wire harness manufacturing system is a similar conveyor system as shown in Figure 3.1. The motion of the conveyor is paced and cyclic in nature. At the beginning of the cycles, every station proceeds to the next position. The operators might work ahead of schedule or be delayed. According to the open-station concept, when the operator does not finish his or her job, he or she can move with the product to the next station to reduce the backlog. When the operator completes the task before the end of the cycle time, he or she can work ahead of schedule [173]. Production stops when the delay exceeds a critical limit. Contrary to this open station-type operating strategy, close-station production is referred to when the operator must stop the conveyor even in the event of a minor delay [174].

FIGURE 3.1: The wire harness paced assembly conveyor (often referred to as a rotary) contains assembly tables consisting of connector and clip fixtures [175].

The key idea is that in the case of modular production, the expected activity times are estimated based on the Bill of Materials (BoM) of the manufactured products. The manufacturing is modular meaning that the products $p_1, \ldots, p_{N_p}$ are built from the set of modules $m_1, \ldots, m_{N_m}$ [176]. The structures of the products are defined by a **P**-matrix (also referred to as a binary/logical matrix) consisting of N_p rows and N_m columns, and the element $p_{i,j}$ of **P** is set to one when the p_i-th type of product contains the m_j-th module (otherwise it is 0). The calculation of the theoretical activity times is estimated based on which $a_1, \ldots, a_{N_a}$ activities are needed to be performed and which $c_1, \ldots, c_{N_c}$ components should be built in at the $w_1, \ldots, w_{N_w}$ workstations. This information is represented in the logical matrix **M** that contains the activities required to produce a given product. As is shown in Table 3.1, the **C** matrix stores which components are built in in each activity, while the **W** matrix assigns activities to the workstations. The specific activity times and factors influencing them were determined based on expert knowledge [172] as presented in Table 3.2. The matrix **T** provides information on the category of the activity describing how the activities are classified into the activity types $t_1, \ldots, t_{N_t}$. The sequence of the products is represented by a π vector of the labels of the types, so $\pi(k) = p_j$ states that type product p_j started to be produced during the k-th production cycle.

TABLE 3.1: The logical matrices defined for performance monitoring.

Notation	Nodes	Description	Size
A	product (**p**) - activity (**a**)	activity required to produce a product	$N_p \times N_a$
W	activity (**a**) - workstation/machine (**w**)	workstation assigned for an activity	$N_a \times N_w$
B	product (**p**) - component/part (**c**)	component/part required to produce a product	$N_p \times N_c$
P	product(**p**) - module (**m**)	module/part family required to produce a product	$N_p \times N_m$
C	activity (**a**) - component (**c**)	component/part built in or processed in an activity	$N_a \times N_c$
M	activity (**a**) - module (**m**)	activity required to produce a module	$N_a \times N_m$
T	activity (**a**) - activity type (**t**)	category of the activity	$N_a \times N_t$
$\mathbf{S}^w$	activity (**a**) - measured time interval ($\mathbf{z}^w(k)$)	activity involved over a measured time interval	$N_a \times l_w$

TABLE 3.2: Types of activities and the related activity times according to [172]. The activity times are calculated using a direct proportionality approach, e.g., when an operator is laying four wires over one foot, proportionally to the parameter t_4, the activity time will be $1 \times 6.9s + 4 \times 4.2s = 23.7s$.

ID	Activity	Unit	Time [s]
t_1	Point-to-point wiring on chassis	Number of wires	4.6
t_2	Laying in U-channel		4.4
t_3	Laying flat cable		7.7
t_4	Laying wire(s) onto harness jig		6.9
		Per wire	4.2
t_5	Laying cable connector (one end) onto harness jig		7.4
		Per wire	2.3
t_6	Spot-tying onto cable and cutting		16.6
t_7	Lacing activity		1.5
t_8	Taping activity		6.8
t_9	Inserting into tube or sleeve		3.0
t_{10}	Attachment of wire terminal		22.8
t_{11}	Screw fastening of terminal		17.1
t_{12}	Screw-and-nut fastening of terminal		24.7
t_{13}	Circular connector		11.3
t_{14}	Rectangular connector		24.0
t_{15}	Clip installation		8.0
t_{16}	Visual testing		120.0

To ensure fully reproducible results, only openly available information on wire harness manufacturing technologies was utilized during the development of this case study.

Based on the data published in [171, 172], the number of types of products N_p is assumed to be 64 and defined as the combination of $N_m = 7$ modules: base module m_1, left- or right-hand drive m_2, normal/hybrid m_3, halogen/LED lights m_4, petrol/diesel engine m_5, 4 doors/5 doors m_6, and manual or automatic gearbox m_7. The number of activities/tasks N_a is defined as 654 and categorized into $N_t =$ 16 types of activities. The time consumptions of these activities are approximated using a direct proportionality approach with regard to the primary activities (see Table 3.2). During the activities involved in the production of the base harness 115 different part families (component types, N_c) are built in (among these $C_t =$ 162 terminals, $C_b = 63$ bandages, $C_c = 25$ clips, and $C_w = 89$ wires). The conveyor consists of 10 workstations (tables, N_w). For every table (workstation) one operator is assigned, therefore, $N_o = 10$.

Hereinafter, the term primary activity time denotes the estimated average period of time required for a certain type of activity to be performed, while the term local activity time refers to the time period required by a specific operator at the w-th workstation to perform the activity in question. The structure of the developed production-monitoring model is determined by the available information [172]. The proposed matrix-based mathematical formulation is beneficial as it allows the compact estimation of the individual $\hat{y}_i^w(k), i = 1, \ldots, N_a$ activity times in every k cycle step (discrete time):

$$\hat{y}_i^w(k) = [\mathbf{t}_i, \mathbf{c}_i]\, \mathbf{x}^w(k)\,, \tag{3.1}$$

as the time consumption of the i-th activity depends on how many elementary activities of a given type should be performed (represented as $\mathbf{t}_i$ which is the i-th row of the matrix $\mathbf{T}$), the number of built in components (the row vector $\mathbf{c}_i$ is the i-th row of the matrix $\mathbf{C}$) and the 'efficiency' of the operator $\mathbf{x}^w(k)$, which is the vector of the estimated local activity times. Therefore, the aim of our investigation is to provide a continuous local estimate of this state vector and its workstation independent $\mathbf{x}(k)$ version providing a reference value and the opportunity for the isolation of operator-independent problems.

3.1.2 Fixture sensor- and indoor positioning system-based activity-time measurements

To measure the activity times, fixture sensors were designed as depicted in Figure 3.2. The fixture-based activity sensors generate timestamps when the component is inserted into the fixture. The sensors on an illustrated assembly table are shown in Figure 3.3, where the fixtures labeled with gray text are inactive as there are no related activities at the depicted workstation.

The fixtures were positioned based on how the measurable activities at the workstations are distributed. For example, the sensor f_1 sends a timestamps when the operator inserts the component c_1 which represents the starting time of the first activity a_1. Details concerning the placement of the sensors are given in Table 3.3.

The activity-dependent sequence of the timestamps recorded by the active sensors in the k-th cycle of the conveyor is represented by vector which serves as the raw input of the performance-monitoring algorithm:

$$\mathbf{s}(k) = [s_1(k), \ldots, s_j(k) \ldots, s_{N_s}(k)]^T \tag{3.2}$$

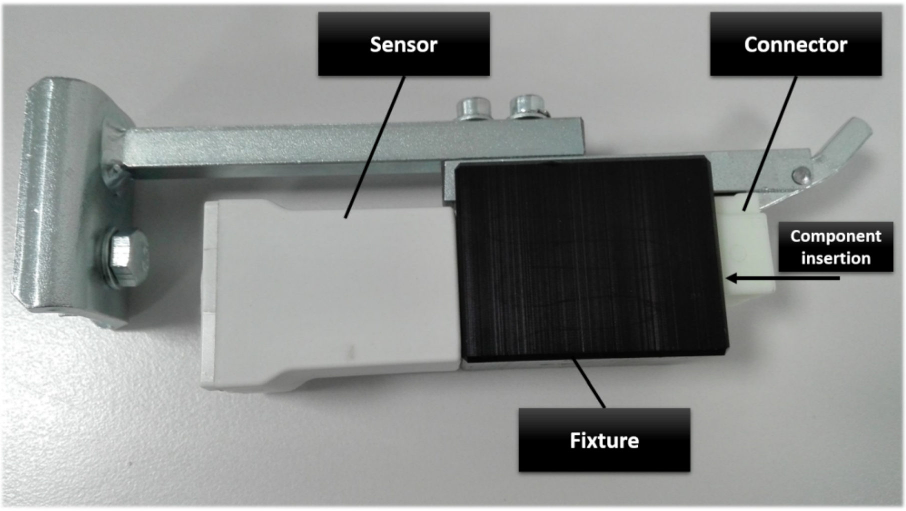

FIGURE 3.2: The designed connector fixture sends timestamps when the operator inserts a component into a fixture.

TABLE 3.3: The placement of the sensors is defined based on the activity IDs. As can be seen in the table, not all the f_i $i = 1, \dots, 16$ fixtures are active at every w_j $j = 1, \dots, 10$ workstation.

Sensor ID	$\boldsymbol{w_1}$	$\boldsymbol{w_2}$	$\boldsymbol{w_3}$	$\boldsymbol{w_4}$	$\boldsymbol{w_5}$	$\boldsymbol{w_6}$	$\boldsymbol{w_7}$	$\boldsymbol{w_8}$	$\boldsymbol{w_9}$	$\boldsymbol{w_{10}}$
f_1	1	79	159							
f_2	12	90	170							
f_3	21	99	175							
f_4	31	109	181							
f_5	44	121	185	226						
f_6								422	486	595
f_7								438	514	603
f_8								448	535	
f_9								451	540	615
f_{10}		132	192		275	324	373	453		
f_{11}					323	372		482		
f_{12}							419			
f_{13}										617
f_{14}										630
f_{15}									547	
f_{16}										654

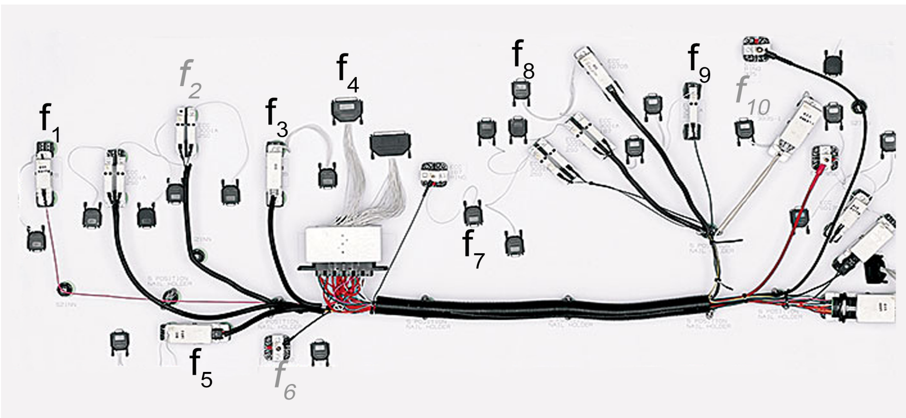

FIGURE 3.3: Illustration of the distribution of the fixtures (f) on an assembly table. As the fixtures move according to the tables of the conveyor system, the fixtures are identically placed at every workstation. The fixtures labeled with gray text are inactive as there are no related activities at the depicted workstation.

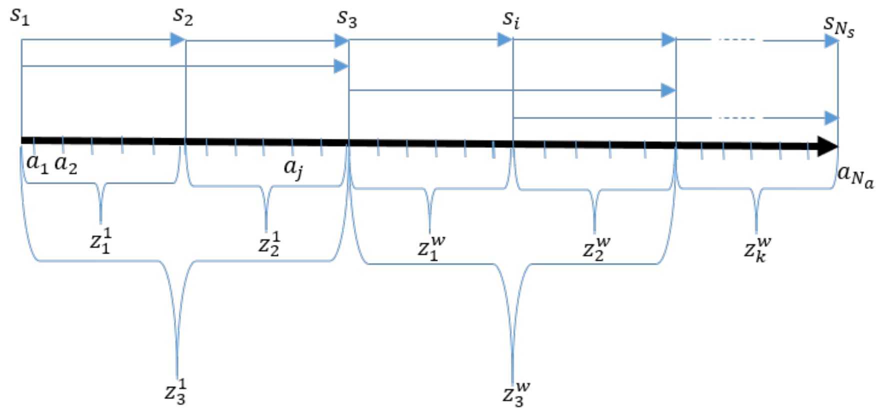

FIGURE 3.4: The concept of activity time measurements. The differences between the timestamps (s_i) define the time period required by a set of activities (a_j), the totals of which are considered as measured variables at each workstation (z_i^w), where w represents the index of the workstation.

As is shown in Figure 3.4, two timestamps clasp a set of activities, therefore, the $z_i^w(k) = s_{\beta(i)}^w(k) - s_{\alpha(i)}^w(k)$ difference between any two timestamps provides the sum of the activity times that are situated between the two sensors. If the timestamps $s_{\alpha(i)}^w(k)$ measures the start of the first activity at the w-th workstation, the station time of the w-th workstation can be measured as $z_i^w(k) = s_{\alpha(i)}^w(k+1) - s_{\alpha(i)}^w(k)$. Based on this concept, a set of measurements can be defined for the workstations $\mathbf{z}^w(k) = \left[z_1^w(k), \ldots, z_i^w(k), \ldots z_{l_w}^w(k)\right]^T$ which is much more interpretable and applicable information with regard to activity-time monitoring than the $\mathbf{s}(k)$ values of the raw measurements.

To put $\mathbf{z}^w(k)$ into context, the information on which products are assembled at each station and the details of the activities that are assigned to the measured time interval $z_i^w(k)$ are required.

The assignment of the activities and the measured time intervals are represented by a set of logical matrices $\mathbf{S}^w$ (see Table 3.1). In the case of modular production the set of activities $\mathbf{q}_a = \mathbf{M}\mathbf{p}_p^T$ should be calculated based on which modules are included in the produced p-th product (represented as $\mathbf{p}_p$ which is the p-th row of the product-module matrix $\mathbf{P}$) and whose activities are required to produce the modules (such information is stored in the relation matrix $\mathbf{M}$). The activities that are assigned to the $\mathbf{z}^w(k)$-th intervals are defined by the operation $diag(\mathbf{q}_a)\mathbf{S}^w$.

$\mathbf{T}^T diag(\mathbf{q}_a)\mathbf{S}^w$ groups the activities according to activity types, while the number of components installed over a specific time interval is calculated as $\mathbf{C}^T diag(\mathbf{q}_a)\mathbf{S}^w$, which can also be grouped by activity types according to $\left(\mathbf{T}^T\mathbf{C} > 0\right) \mathbf{C}' diag(\mathbf{q}_a)\mathbf{S}^w$.

Based on the proposed matrix-type representation, the estimated time intervals at the w-th workstation can be calculated as:

$$\hat{\mathbf{z}}^w(k) = \left[\mathbf{T}^T diag(\mathbf{q}_a)\mathbf{S}^w \,, \left(\mathbf{T}^T\mathbf{C} > 0\right) \mathbf{C}^T diag(\mathbf{q}_a)\mathbf{S}^w\right] \mathbf{x}^w(k) = \mathbf{H}^w(k)\mathbf{x}^w(k) \quad (3.3)$$

The model equation $\mathbf{z}^w(k) = \mathbf{H}^w(k)\mathbf{x}^w(k)+\mathbf{e}^w$ and the related measurements $\mathbf{z}^w(k)$ can be used for the continuous estimation of the vector of operator efficiencies (namely estimated local activity times), $\mathbf{x}^w(k)$, where $\mathbf{e}^w(k)$ is assumed to be a serially uncorrelated white-noise vector of observational errors with covariance matrix $\mathbf{R}^w(k)$.

As $\mathbf{H}^w(k)$ depends on the actual product, which product is produced at the w-th workstation must be tracked. For the localization of the products and identification of the status of the conveyor system, an Ultra-Wide band (UWB) IPS technology with its low energy demand for transmitting information over a broad bandwidth ($>$ 500 MHz) and accuracy within the range of 30–50 cm, which is significantly better than the uncertainty of one meter that the Bluetooth Low Energy (BLE)-based solutions posses [177, 178], was applied.

In comparison with outdoor environments, sensing location information in indoor environments requires higher precision which is a more challenging task because various objects reflect and disperse signals. UWB is an emerging technology in the field of indoor positioning [96] that has shown better performance compared to others [179] even in the presence of severe multipath [180, 181]. Depending on the positioning technique, the angle of arrival (AoA), the signal strength (SS), or time delay information can be used for positioning [178]. Received signal strength (RSS) UWB positioning methods also can be divided into Time of Arrival (ToA) and AoA [182].

The concept of identification of the products at workstations to extract product-relevant information from the BoM and other structured information sources are widely used to support production management [183], value stream mapping [184], and IIoT-based lifecycle management [185]. In the developed system the IPS beacons are mounted to the flat wire-harness and the raw signals of the receivers (shown in Figure 3.5) are processed to assign the cables to the workstations.

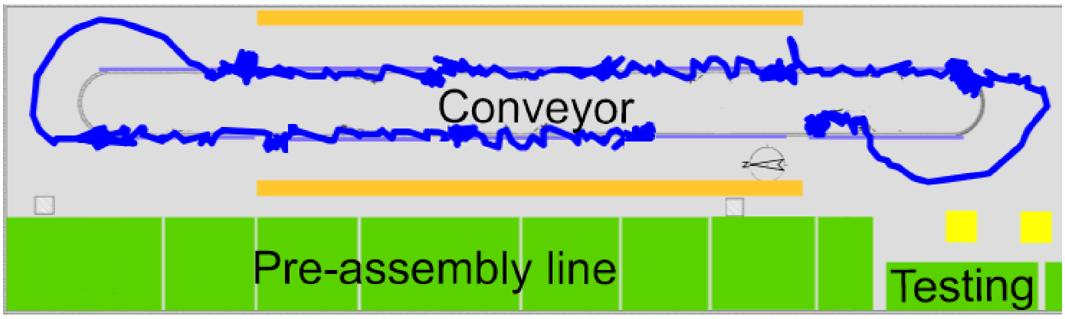

FIGURE 3.5: Illustration of how the IPS tracks a product in the conveyor at the table. The tracking is accurate and nicely depicts the rotations of the table at the edges of the conveyor.

3.1.3 Multi-sensor data fusion-based recursive estimation

Multiple sensors provide redundancy which enables the robust recursive estimation of the unmeasured primary activity times of the operators. Therefore, the estimation problem is defined as a sensor-fusion task [186]. The presented sensor fusion algorithm combines all sensory and production data such that the estimates of the activity times have less uncertainty than would be possible when these sources were used individually. The elements of the monitoring system are structured as shown in Figure 3.6, where the local estimations are used to evaluate the operator's performance and the FDI (Fault Detection and Isolation) to monitor the full processes.

The fusion center receives and synchronizes all the $\mathbf{z}^w(k), w = 1, \ldots, N_w$ measured time intervals and the related $\mathbf{H}^w(k), w = 1, \ldots, N_w$ time-variable regressors, which means all data collected from the workstations are time-stamped and arranged according to k-th cycle of the conveyor:

$$\mathbf{z}(k) = \begin{bmatrix} \mathbf{z}^1(k) \\ \vdots \\ \mathbf{z}^{N_w}(k) \end{bmatrix}, \mathbf{H}(k) = \begin{bmatrix} \mathbf{H}^1(k) \\ \vdots \\ \mathbf{H}^{N_w}(k) \end{bmatrix}, \tag{3.4}$$

The linear structure of the developed production-monitoring model (see Equation (3.1)) is adequate for the studied problem as the time consumption of the activities linearly depend on how many elementary activities should be performed and what is the number of the built in components [172]. When a linear sensor-fusion model

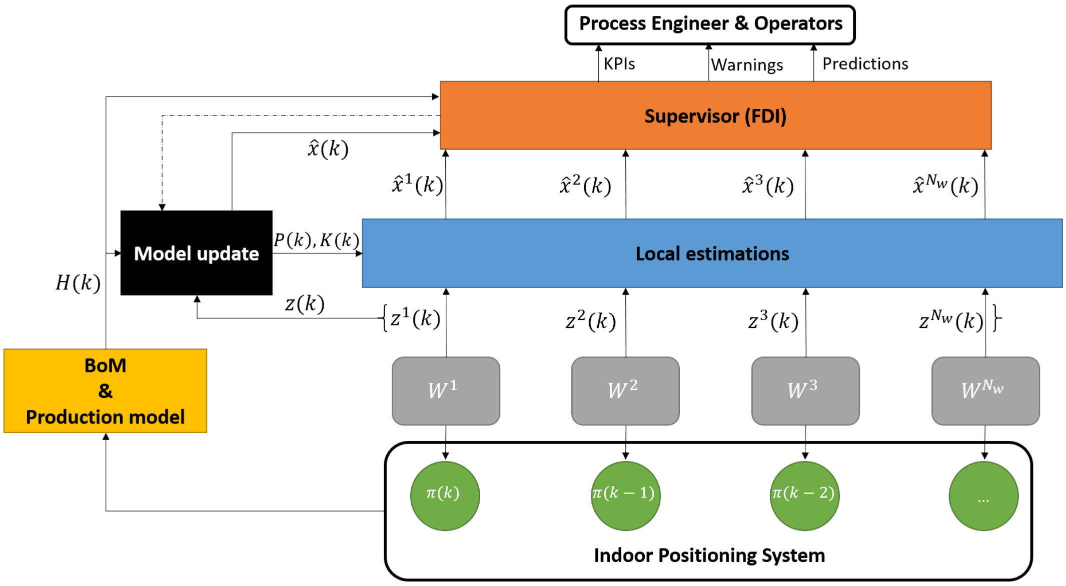

FIGURE 3.6: The sensor fusion-based architecture of the proposed monitoring system. The local (operators individual performance) and global (full production line) monitoring are available with this complex architecture.

is assumed, the previously presented linear time-variant model can be represented as

$$\mathbf{z}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{e}(k)\,, \tag{3.5}$$

where the $\mathbf{e}(k)$ noise vector of the fused observations consists of the $\mathbf{e}^w(k)$ serially uncorrelated white-noise vectors of observational errors at the workstations, $\mathbf{e}(k) = \left[(\mathbf{e}^1(k))^T, \ldots, (\mathbf{e}^{N_w}(k))^T\right]^T$.

When the observation errors of the workstations are assumed to be independent, the covariance of the $\mathbf{e}(k)$ noise vector is a block diagonal matrix defined as $\mathbf{R} = diag\left(\mathbf{R}^1, \ldots, \mathbf{R}^{N_w}\right)$.

The central estimation enhances the confidence of the nominal model which improves the performance of fault detection based on the reconciliation of the local measurements [187].

Based on $k = 1, \ldots, N$ synchronized $\mathbf{z}(k)$ and $\mathbf{H}(k)$ observations the objective function of the central estimation problem can be formalized as:

$$\hat{\mathbf{x}}(N) = \arg\min_{\mathbf{x}} V_N(\mathbf{x})\; V_N(\mathbf{x}) = \frac{1}{N}\sum_{k=1}^{N}\left[\mathbf{z}(k) - \mathbf{H}(k)\mathbf{x}\right]^T \mathbf{Q}\left[\mathbf{z}(k) - \mathbf{H}(k)\mathbf{x}\right]. \tag{3.6}$$

When the positive-definite weighting matrix $\mathbf{Q}$ is defined as $\mathbf{Q} = (\mathbf{R})^{-1}$, the estimation is equivalent to the maximum-likelihood cost function [188].

The covariance matrix of the estimation error $\tilde{\mathbf{x}}(k) = \hat{\mathbf{x}}(k) - \mathbf{x}(k)$ is:

$$E\left(\tilde{\mathbf{x}}(N)\tilde{\mathbf{x}}^T(N)\right) = \mathbf{P}^*(N) = \left[\sum_{k=1}^{N} \mathbf{H}^T(k)\mathbf{R}^{-1}\mathbf{H}(k)\right]^{-1} \tag{3.7}$$

The recursive estimation of the primary activity times $\mathbf{x}(k)$ is similar to the state estimation algorithm which assumes the following Gauss-Markov (GM) process:

$$\mathbf{x}(k) = \mathbf{A}^*(k)\mathbf{x}(k-1) + \eta(k-1),\ \ \eta(k) = \mathcal{N}(\mathbf{0}, \mathbf{Q}_x) \tag{3.8}$$

$$\mathbf{z}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{e}(k),\ \ \mathbf{e}(k) = \mathcal{N}(\mathbf{0}, \mathbf{R}) \tag{3.9}$$

where $\eta(k)$ noise vector and its $\mathbf{Q}_x$ covariance matrix represents the uncertainty of the unknown and time-varying parameters and $\mathbf{A}^*(k)$ stands for the state transition matrix of this random process.

The recursive estimation consists of prediction and correction steps as follows.

At the prediction step the state vector and its covariance matrix is calculated based on information available at the $k-1$ time instant:

$$\hat{\mathbf{x}}(k-1) = \hat{\mathbf{x}}(k-1) \tag{3.10}$$

$$\mathbf{P}^*(k-1) = \mathbf{P}^*(k-1) + \mathbf{Q}_x \tag{3.11}$$

The correction step utilizes the measured $\mathbf{z}(k)$ measurements at the correction the estimated state variables by the $\mathbf{e}(k) = [\mathbf{z}(k) - \mathbf{H}(k)\hat{\mathbf{x}}(kk-1)]$ prediction error, with the $\mathbf{K}(k)$ time-varying Kalman gain updated based on the refreshed $\mathbf{P}^*(k)$ covariance matrix:

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}(k-1) + \mathbf{K}(k)\left[\mathbf{z}(k) - \mathbf{H}(k)\hat{\mathbf{x}}(k-1)\right] \tag{3.12}$$

$$\mathbf{K}(k) = \mathbf{P}^*(k-1)\mathbf{H}^T(k)\left[\mathbf{R} + \mathbf{H}(k)\mathbf{P}^*(k-1)\mathbf{H}^{*T}(k)\right]^{-1} \tag{3.13}$$

$$\mathbf{P}^*(k) = \mathbf{P}^*(k-1) - \mathbf{K}(k)\mathbf{H}(k)\mathbf{P}^*(k-1) \tag{3.14}$$

3.1.4 Local estimation and monitoring of the primary activity times

To constrain the model parameters to lie within a reliable region and incorporate important *a priori* knowledge of the activity times, the estimated parameters were optimally projected on to the set of linear constraints by quadratic programming [170].

The local (operator-related) projection of the unconstrained estimate $\hat{\mathbf{x}}(k)$ can be considered as a quadratic programming problem:

$$\hat{\mathbf{x}^w}(k) = arg \min_{\mathbf{x}(k)} [\mathbf{x}(k) - \hat{\mathbf{x}}(k)]^T \mathbf{Q}_p [\mathbf{x}(k) - \hat{\mathbf{x}}(k)] \tag{3.15}$$

subject to:

$$\mathbf{A}_e^w(k)\mathbf{x}(k) = \mathbf{b}_e^w(k) \tag{3.16}$$

$$\mathbf{L}^w\mathbf{x}(k) \leq \mathbf{c}^w \tag{3.17}$$

$$\hat{\mathbf{x}}(k)^c = \hat{\mathbf{x}}(k) - \mathbf{P}^*(k)\mathbf{H}_j^T\mu_j - \mathbf{P}^*(k)\mathbf{L}_j^T\lambda_j \tag{3.18}$$

where $\hat{\mathbf{x}}(k)$ denotes the unconstrained solution, $\hat{\mathbf{x}}(k)^c$ denote the constrained solution, $\mathbf{A}_e^w(k)$ and $\mathbf{b}_e^w(k)$ define the linear equality constraints, while $\mathbf{L}^w(k)$ and $\mathbf{c}^w(k)$ represent the linear inequalities. μ_j and λ_j are vectors of Lagrange multipliers associated with equality and inequality constraints. This formulation ensures the optimal (least squares correction) when $\mathbf{Q}_p = (\mathbf{P}^*(k))^{-1}$. When $\mathbf{Q}_p$ denotes the identity matrix an orthogonal projection is obtained. Assuming the constraints are true, parameter bias can never be increased [170].

The following section demonstrates how the estimated and expected primary activity times are used for production monitoring.

3.2 Wire harness case study

To validate the reliability of the proposed model, the distribution of the activity times collected from real production lines was studied. As is illustrated in Figure 3.7 the distribution of the assembly times can be broken down into several Gaussian-type distributions. The distribution is not bimodal because the lower outliers are neglected.

3.2.1 Online monitoring of operator performance

When the raw material, design or the processing of a component in a cost-cutting or quality-improvement project is changed by the supplier, this change may influence the activity times of the operators. The identifiability of the model is determined by the rank of the covariance matrix $\mathbf{P}^*(N)$. When the rank is smaller than the number of measurements (which occurs when the individual performance of operators is estimated at a specific workstation) only a subset of the parameters is identifiable.

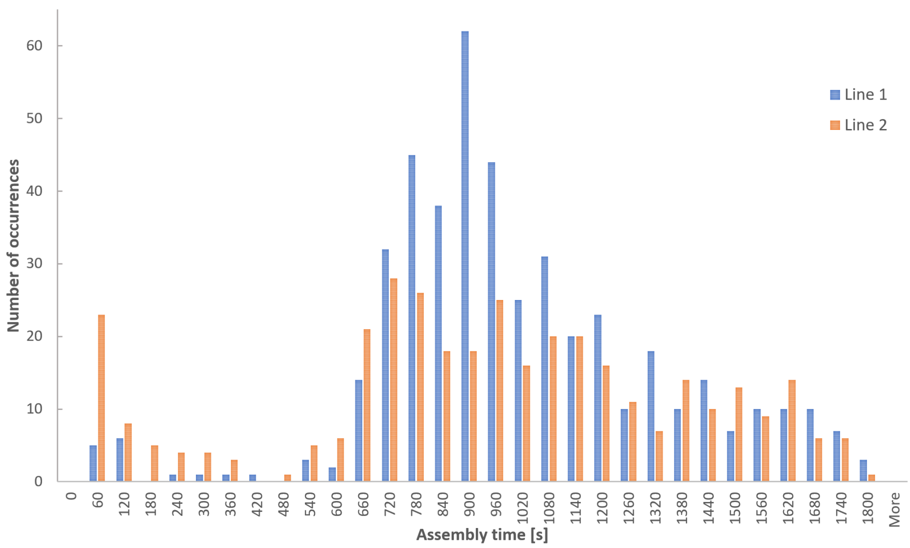

FIGURE 3.7: The histogram of measured processing times in two different conveyors (production lines). The histograms indicate that the distribution of the sensor-delivered processing times can be decomposed into normal distribution functions according to different products.

The information content of the available data can be evaluated based on the eigenvalues or determinant of the covariance matrix $\mathbf{P}^*(N)$. The tools of D-optimal experimental design that tries to maximize the determinant of $\mathbf{F}^*(N)$ which is identical to the minimization of the determinant of $\mathbf{P}^*(N)$ where utilized.

$$\mathbf{F}^*(N) = (\mathbf{P}^*(N))^{-1} = \sum_{k=1}^{N} \mathbf{H}^T(k)\mathbf{R}^{-1}\mathbf{H}(k) \tag{3.19}$$

When only one product is produced, $\mathbf{H}(k)$ does not change in terms of time. In this case, the set of the identifiable parameters for a given product can be determined by the QR decomposition of $\mathbf{H}(k)$ (or $\mathbf{H}^w(k)$ when a local estimation is needed). When different products are produced, the variation in $\mathbf{H}(k)$ significantly increases the available information, so the optimization of the production sequence can highly influence the identifiability of the model and confidence in the parameters ($\mathbf{P}^*(N)$, $\pi(k)$).

The production of 1000 products was studied. The production sequence contained all 64 types of products with an average batch size of 10 products/batch. The rank of the covariance matrix $\mathbf{F}^*(N)$ was identical to the size of $\hat{\mathbf{x}}(k)$, so all activities could be monitored (see Figure 3.8).

Such operator-independent loss in performance can occur when a shorter length of wire increases the time required to lay and arrange the cables. In this case study, such effects are monitored. In the studied case, the new wires between the c_{87} and c_8 components are a bit shorter than specified. The component c_{87} (seal on the terminal) has an impact on the t_{10} type of activity in the module m_4 which increases the related primary activity time ($x_{10}(k)$) by 15% at the 200th product, while the component c_8 (the shorter wire) has an impact on the activity type t_5 in the module m_2, which increases the related $x_5(k)$ state variable by 20% after the 300th product. In this illustrative scenario the quality inspection time decreases after the 500th product.

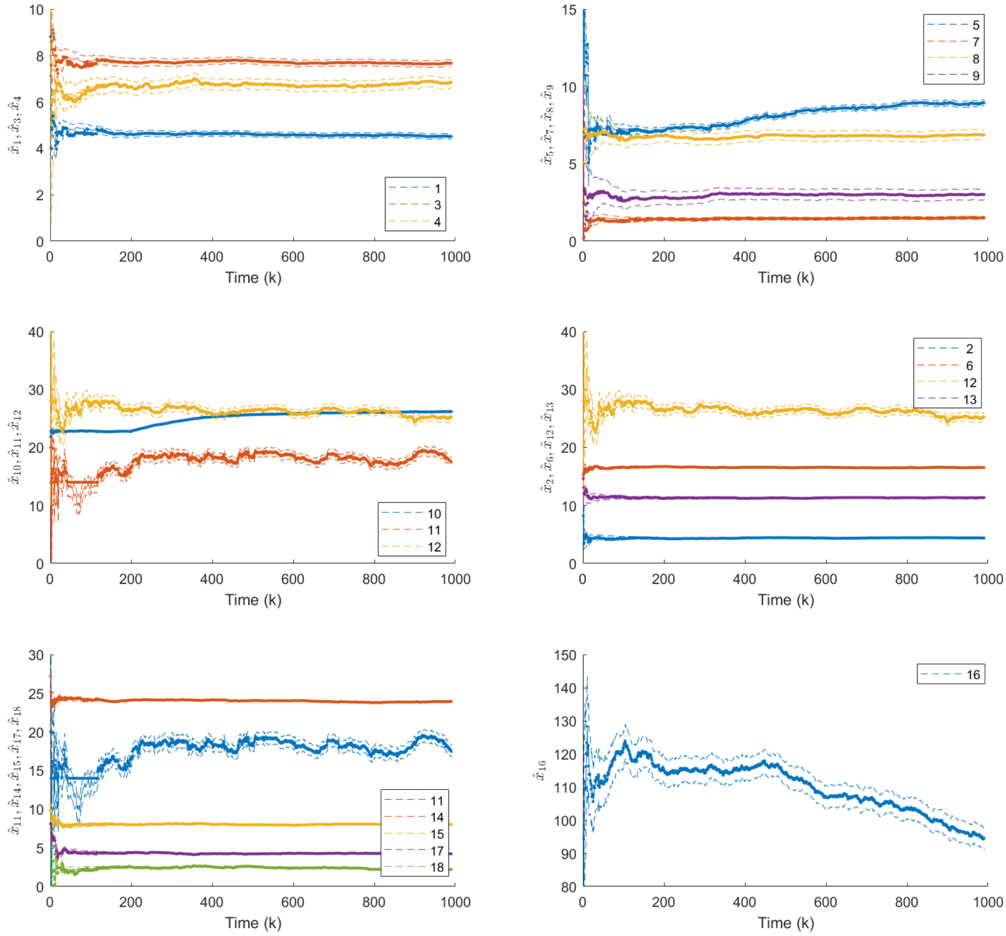

FIGURE 3.8: Estimated primary activity times with their $p = 0.01$ confidence intervals (represented by dashed lines). The figure illustrates that the algorithm is able to track the changes in the $x_{10}(k)$, $x_5(k)$ and $x_{16}(k)$ activity times after the 200th, 300th and 500th product, respectively. The bold lines represent the constrained parameter estimates and the y axis is the activity times in seconds, the x axis is the cycles.

As Figure 3.8 illustrates, the proposed system is able to track the slowed and fastened activities. The cycles are noted with $Time(k)$. The benefit of the proposed constrained algorithm is clearly visible, the estimated variables converge faster and are always reliable.

The means of detecting individual losses in operator performance losses and sensor faults (due to delayed registration and IIoT communication) were also studied.

In terms of fault detection, the prediction error used in Equation (3.6) can be used as generates an interpretable and easily traceable univariate time series that reflects the global performance of the model.

The global performance of the model is reflected by

$$e_q(k) = [\mathbf{z}(k) - \mathbf{H}(k)\mathbf{x}]^T \mathbf{Q} [\mathbf{z}(k) - \mathbf{H}(k)\mathbf{x}] \ , \tag{3.20}$$

while the local, workstation related fault detection should be based on the local observations:

$$e_q^w(k) = [\mathbf{z}^w(k) - \mathbf{H}^w(k)\mathbf{x}]^T \mathbf{Q}^w [\mathbf{z}^w(k) - \mathbf{H}^w(k)\mathbf{x}^w] \ , \tag{3.21}$$

where $\mathbf{Q}^w$ represents the wth block matrix of $\mathbf{Q}$.

Based on the analysis with regard to the rank of the $\mathbf{H}^w(k)$ matrices, the observable sets of activities were determined. As is illustrated in Figure 3.9, at the $w = 2$ workstation the time consumption of six primary activities are observable. The proposed algorithm was able not only to detect operator-dependent problems (of the 250th product) related to these activities, but by monitoring the $e_q(k)$ it was possible to determine when sensor faults occurred (see the bottom of the figure). The parameters of the gross error detection algorithm can be fine-tuned by Monte Carlo simulation and detailed analysis of the distribution of the modeling error [189, 190] (the demonstration of the applicability of these techniques in this problem is out of the scope side this thesis).

As is illustrated in Figures 3.10 and 3.11, the calculations above can be used to estimate the expectable operation times for all workstations, check how well the process is balanced and how the complexity of the product influences the workloads of the workstations. Left diagram on the Figure 3.11 shows the minimal version of the product (p_1), while the right is the most complex (p_64). With the help of this model the effect of the changes in the activity time can be immediately calculated on the tack-time and the effectiveness of the operators. The presented example demonstrated that in the event of good estimates with regard to the duration of the primary activities and with the help of the IIoT-based fusion of product-relevant information, real-time data for OEE calculations can be provided.

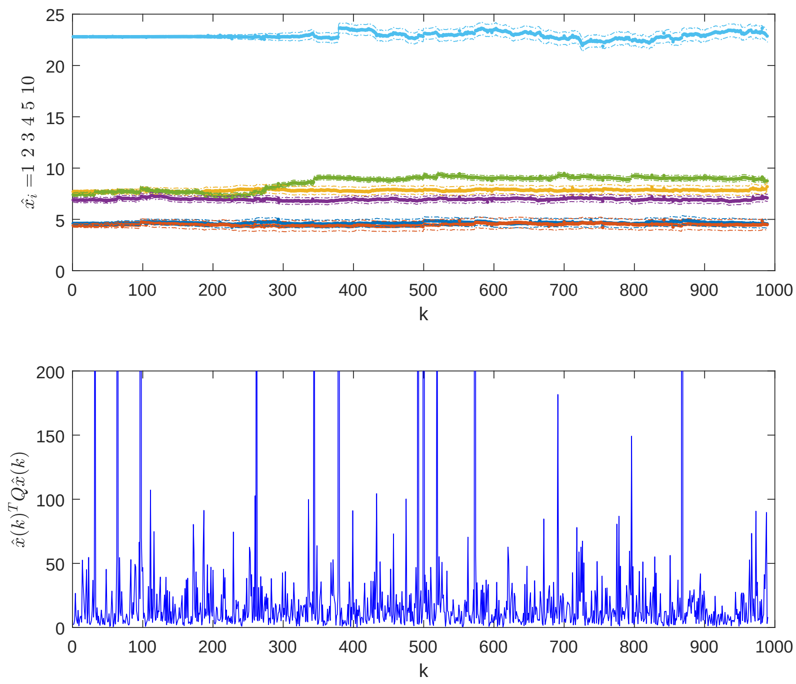

FIGURE 3.9: Fault-detection performance at the 2nd workstation. The upper figure illustrates that the algorithm is able to detect operator-dependent problems (after the 250th product).

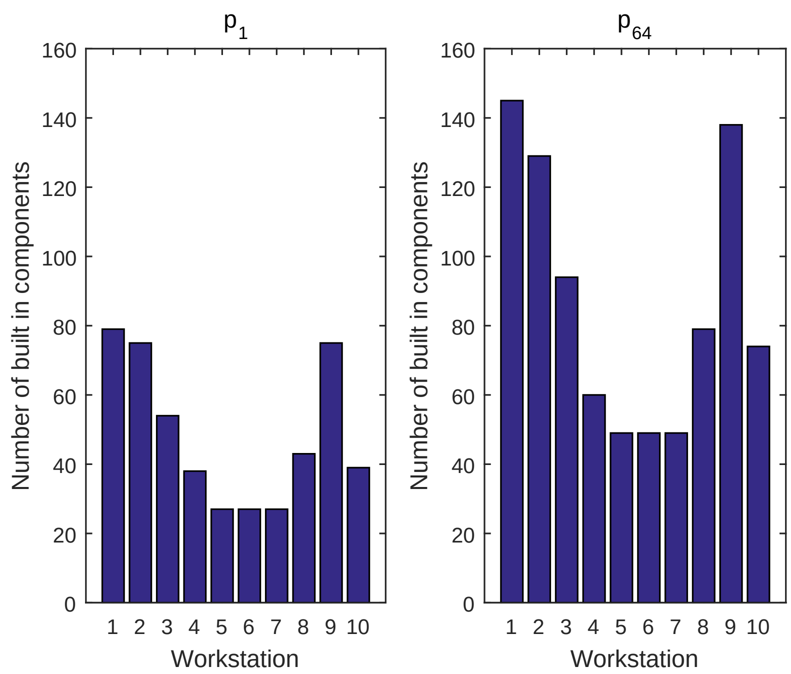

FIGURE 3.10: The number of the built-in components at a given workstation. The figure shows how the workload differs during the production of the base module (p_1) and the most complex product (p_{64}).

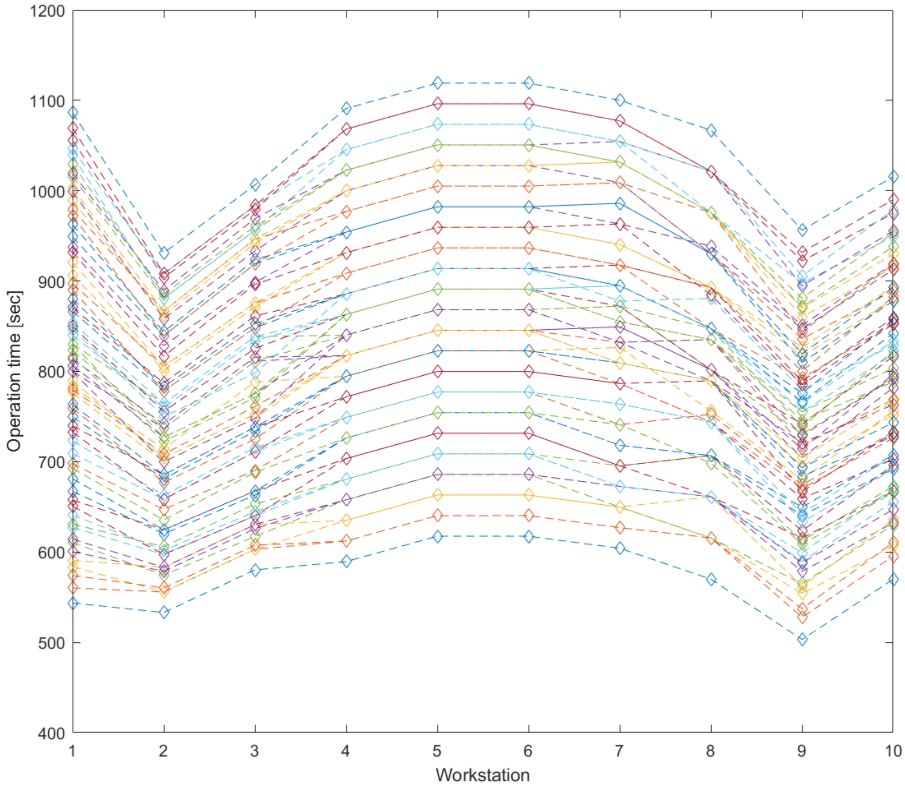

FIGURE 3.11: The variability of the station times during the production of the 64 product. The figure illustrates how the production line is balanced and how the complexity of different products influences the station times. The connection between the diamonds notation is for to help the understanding. These are discrete values.

The most important key performance indicators (KPIs) of the production system are the station times which reflect how well the production line is balanced. The balancing of a modular production system is a challenging industrial problem due to the great diversity of products [25]. As the station times are the functions of the manufactured products, which product is assembled on a given workstation must be followed. The calculation of the station time is similar to the calculation of the estimated sum of activity times between two fixture sensors (Equation (3.3)), namely the difference between the appropriate timestamps recorded by the fixture sensors:

3.3 Conclusion of activity-time monitoring

Human-in-the-loop cyber-physical production systems are transforming the industrial workforce. Due to the enormous variability and complexity of products, the tracing of hundreds of activity times on production lines is a critical problem. To handle this problem a software-sensor-based activity-time and performance measurement system was proposed. To ensure a real-time connection between operator performance and varying degrees of product complexity fixture sensors were utilized and designed. An indoor positioning system used to merge this multi-sensor data with product-relevant information.

The presented sensor fusion algorithm combines all sensory and production data such that the estimates of the activity times have less uncertainty than would be possible when these sources were used individually. The estimation of the activity times is based on a linear-in-parameters model. The linear structure of the developed production-monitoring model is adequate as the time consumption of the activities linearly depend on how many primary activities should be performed and what is the number of the built-in components.

The number of parameters of activity time estimation models is comparable to the number of measurements, the identifiability of the parameters of the model has to be carefully analyzed. For this purpose, I studied the Fisher information/-covariance matrix of the estimation problem. The identifiability of the model and the information content of the available data can be evaluated based on the rank, the eigenvalues and the determinant of the covariance matrix. When the rank is smaller than the number of measurements (which occurs when the individual performance of operators is estimated at a specific workstation), only a subset of the parameters is identifiable. As the placement of the sensors significantly influences the identifiability of the parameters, tools of D-optimal experimental design can be used to optimize the proposed system.

The determination of the optimal number of sensors and features has crucial importance as redundant sensors can generate correlated features which decrease the efficiency of the algorithm. The analysis of the eigenvalues of the covariance matrix can highlight these negative effects. As this analysis is identical to Principal Component Analysis (PCA) of the multisensor data, the proposed methodology can utilize the reduced and transformed uncorrelated features, which results in a Principal Regression-based process monitoring algorithm. The second approach of avoiding correlated features is the application of feature selection algorithms that should be based on the previously discussed experimental design optimization task.

As the estimation problem can be ill-conditioned and poor raw sensor data can result in unrealistic parameter estimates, constraints were introduced into the parameter-estimation algorithm to increase the robustness of the software sensor.

The proposed model-based performance monitoring system tracks the recursively estimated parameters of the activity-time estimation models, while the sensor-relevant fault detection functionalities are based on the modeling errors which can be evaluated by classical residual-based fault detection algorithms.

The applicability of the proposed methodology is demonstrated on a well-documented benchmark problem of a wire harness manufacturing process. The presented example demonstrated the benefits of multiple sensors as they provide redundancy which enables the robust recursive estimation of the unmeasured primary activity times. The fully reproducible and realistic simulation study also confirmed the efficiency of the proposed constrained estimation algorithm regarding fast convergence and giving reliable estimates.

The results illustrate that indoor positioning system-based integration of product-relevant information and sensor signals and can be efficiently utilized to design on-line performance management systems.

The developed benchmark problem can be used to study fault detection and sensor placement algorithms which is the objective of our further research.

Thanks to the newest IIoT technologies supported constantly improving measurements, the activity times can be monitored more and more accurately enabling process engineers to construct models of optimal complexity that support the control of production with the required degree of precision and accuracy. Thanks to this development the results can be easily generalised and widely utilised, e.g., by the next Chapter presented model-based controller can be implemented in the real-time optimisation of supply chains, and the proposed fuzzy activity-time models are easily applicable in the scheduling of uncertain business and production processes, which will form the basis of our future research.

Chapter 4

Reducing machine setup and changeover times by survival analysis

4.1 Introduction

As manufacturing companies increase their flexibility by increasing the variance of the products [191] and reducing lot sizes [192], changeovers are becoming a critical issue [193], as changeovers can lead to unplanned downtimes and significant capacity losses [194]. Since the number of changeovers cannot be significantly minimized, the losses associated with such changeovers should be minimized.

Although some reasons for anomalies can be identified based on observations, for example, incorrect orders, there can be several hidden causes that can be detected only based on the detailed analysis of log data. Furthermore, the detection of anomalies is not sufficient for systematic improvement; continuous development requires performance models and the application of data- and model-based root cause analyses.

In changeover improvement projects, changeovers are divided into small process steps [26]. A changeover is typically composed of three phases: run-down, set-up and run-up [195]. Set-up duration reduction initiatives have been associated with Shingo's single minute exchange of die (SMED) method [196]. The application of

Shingo's methodology usually results in two main benefits: increasing manufacturing capacity and improving equipment flexibility [197]. SMED can be supported by intelligent data-driven techniques; neural networks (NNs) [198], graph theory [199], activity time models [200], and machine learning methods [201] were already utilized in these projects.

Data-driven performance models are built when no detailed knowledge is available about the process [202]. These models can be used for activity-based targeting [203] when the drivers of the performance can be explored by regression models [204].

The minimization of the setup times should also follow data- and model-based approaches. The reduction of the losses should be based on a process model [205]. Process models are based on analysis activities that require resources and time [206]. The analysis of activity times requires activity-time models. When it is relevant, these models should handle how product-relevant issues and competencies of the operators influence the activity times [207]. Based on these requirements, the development of these models should be based on the integration of heterogeneous information about the production [208] and should also handle the stochastic nature of the work of the operators [209].

This Chapter presents how survival analysis can be used to identify probabilistic and dynamic targeting models that can support the work of operators. Our key idea is that survival analysis can generate cumulative distribution functions of the activity times that represent the probability that the activity will be shorter than a given value. Instead of the easily applicably non-parametric Kaplan-Meier distribution [210], the parametric Cox regression-based method is applied [211], as the sensitivity analysis and significance tests of the parameters of the model can be used to identify the root causes of the increased setup and changeover times. The application of the parametric activity-time distribution function is beneficial because it can be easily incorporated into a dynamic performance management system where the expected activity times are compared to the logged activities of the operators.

To the best of our knowledge, the proposed method has never been used before for changeover analysis. In the field of systems engineering, survival analysis is mainly used to build accelerated-failure-time models [212] that can be used for remaining useful life (RUL) estimation [213]. Recently, interesting applications in business process development were also reported, where dropped calls in a helpline [214] and stock selection times [215] were analyzed. This later study is the closest to our work, as the important factors that influence the selection speed were also studied by Monte Carlo simulation. Despite the small number of related studies, we believe that there is a strong need for the identified parametric activity time models. For example, a costing methodology called time-driven activity-based costing uses a formula for calculating the required activity time, which is very similar to what we will propose based on the survival analysis of the activity times of the operators [216].

The remainder of the Chapter is structured as follows. Section 4.2 describes the proposed method. In Section 4.3, a detailed application study is presented based on the analysis of crimping machines. With the help of this case study, the sections will illustrate 1) how information about production should be integrated into the analysis of the changeovers, 2) how the models should be identified and how the proportional hazard assumptions of Cox regression should be checked and ensured, and 3) how the resulting model can be used to evaluate the losses of changeovers and the efficiency of the operators.

4.2 The concept of Cox regression-based root-cause analysis and performance monitoring

This section presents the details of the proposed method. As Figure 4.1 shows, the method starts with the collection and integration of changeover-relevant information. The activity-time related data are extracted from machine logs. Section 4.2.1 discusses how machine and production states, such as production, setup, wait, stop, fault, and short-fault states, can be extracted from these log files. Section 4.2.2 shows how the duration of these states can be processed by survival analysis to identify probabilistic activity-time models and how parameter confidence analysis can be used for root-cause detection of longer changeovers. Finally, Section 4.2.3 presents how the resulting models can be used for performance monitoring.

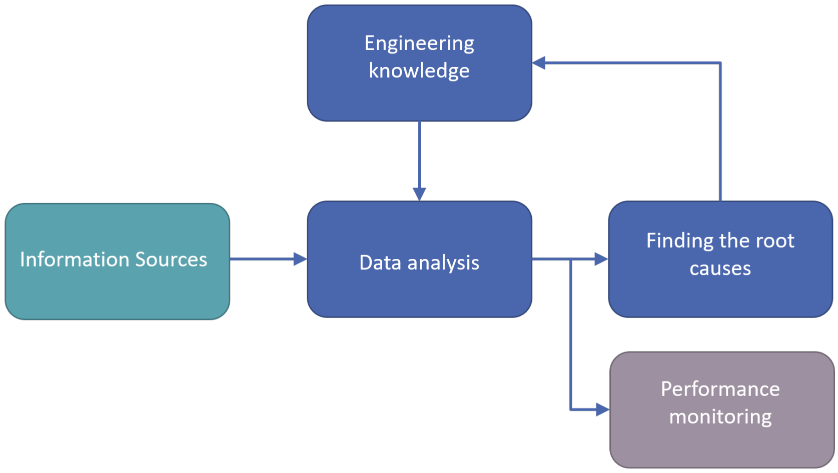

Figure 4.1: The proposed method is based on the fusion of heterogeneous information that characterizes the changeovers. The survival analysis of the integrated log-files can be used for finding the root causes of capacity losses, and the resulting models can also be used for performance monitoring.

4.2.1 Integrated log file

Industry 4.0 solutions utilize the potential of information sharing. The integration of information enables the monitoring and logging of events and their background data to characterize the activities of the operators. For this particular case, the primary sources of this information fusion are illustrated in Figure 4.2.

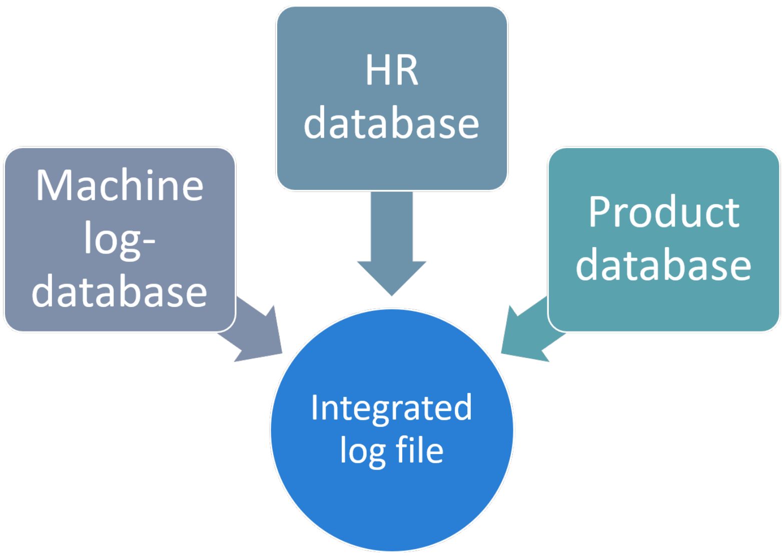

Figure 4.2: The analysis is based on the fusion of information from the machine log files, operator seniority and training data from the HR (human resources) database, and the product parameters from the product database.

Table 4.1 illustrates the integrated variables in the case of the studied wire crimping process. The order ID defines the actual lot. All the details of the product, such as the cross-section and the length of the wire as well as wire and terminal types, are connected to the log file based on this key ID. The operators are identified by operator IDs that are used to connect their seniority stored in the database of the human resources department to the extended log file.

Given that changeover analysis is in focus, four types of events (process steps) are identified. The first step is always the setup-changeover step when the operator prepares all of the necessary materials and tools for the changes. This step is generally the longest because the operator must search the materials on the shop floor. After the setup-changeover step is performed, in a typical case, some samples are selected for learning, which means that the operator sets the crimping force. The setup-short fault step follows every setup-sample operation, which represents the cutting of the sample wire. All steps can be repeated several times, e.g., when the measured value is not satisfied, then the operator needs to cut a new sample.

The sequence of these steps is neither linear nor deterministic. Figure 4.3 shows the BPMN (business process model and notation) model of the whole changeover process. Such a model can be built based on the expert knowledge of the process engineers or can be explored from machine logs by process mining algorithms [217].

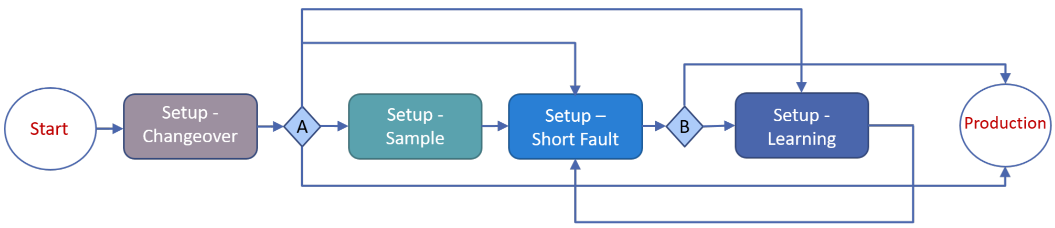

FIGURE 4.3: The process model of the changeover represents how the setup-changeover step is followed by sampling, learning (when the operator sets the crimp force), or short-fault steps. The branches in the process are described in Table 4.2.

4.2.2 Survival-analysis-based activity time modeling

This work focuses on the analysis of the duration of the elementary process steps and the overall changeover process. Due to the nature of the operators and the complexity of the changeover process, stochastic activity time models are identified. The key idea is that the activity times are described by survival functions representing the conditional probability that an activity will last longer than a specific time T, provided that it lasts for a time T [218]:

$$S(t) = P(t \leqslant T \leqslant t + dt | T \geqslant t) \tag{4.1}$$

where T is the survival time (duration of the activity). The primary survival analysis, the Kaplan-Meier method [219], generates an empirical distribution function that can be described by the following equation [211]:

$$S(t) = \prod_{j:t_j \leqslant t} \frac{n_j - d_j}{n_j} \tag{4.2}$$

where n_j represents the number of activities that have not been completed at time instant t_j, while d_j is the number of activities completed between periods t_{j-1} and t_j (as illustrated in Figure 4.4).

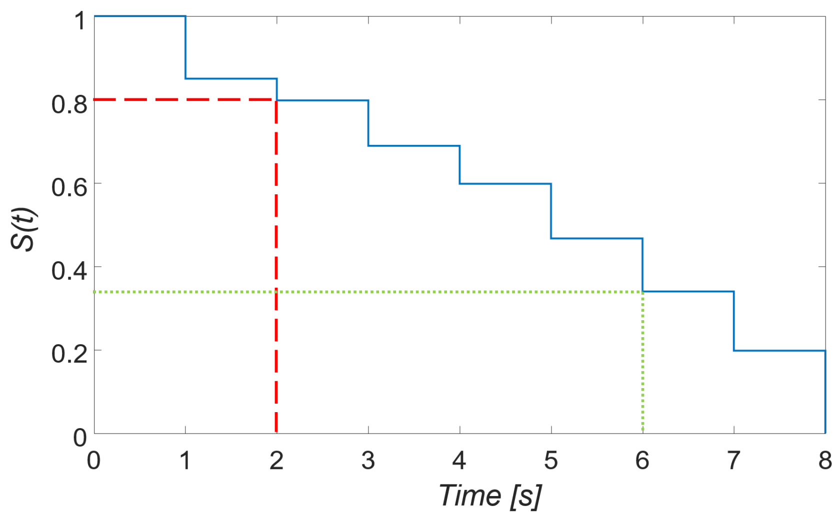

FIGURE 4.4: Example of Kaplan-Meier empirical survival function. In this example, the probability that the event will last longer than 2 seconds is 0.8, while the probability that the event will last longer than 6 seconds is 0.35.

As we are interested in which variables influence the activity times, instead of this nonparametric model, the parametric Cox regression model is used [218]:

$$S(t, \mathbf{x}_k) = [S_0(t)]^{exp[\sum_{j=1}^{n} b_j x_{k,j}]} \tag{4.3}$$

where $S_0(t)$ is the baseline survival function, which is proportionally modified by the $x_{k,j}$ $j = 1, \ldots, n$ number of $x_{k,j}$ features, where $k = 1, \ldots, N$ represents the index of the $\mathbf{x}_k$ vector of the variables that influences the activity times, and b_j denotes the parameters of the regression model.

The available data used for the identification of this model are arranged according to the assumed model structure (see Table 4.3). During the identification of the parameters, the activities that take an unreasonable amount of time can be eliminated by censoring the observations.

The results of the Cox regression can be accepted if the proportional hazard assumption (PHA) is met for each predictor. This means that the effect of the individual predictors must be independent and proportionally influence the activity times. The hypothesis can be verified by examining the Schoenfeld residuals [220]. This statistical test ranks the survival times, as the first event has a value of one, etc. [218]. If these ranks and the Schoenfeld residuals are not correlated with each other, then the PHA is satisfied for the studied predictor.

The assumption can also be visually checked by the log-log or the observed vs predicted (OP) method. In the log-log method, Kaplan-Meier distributions are plotted for every possible value of the individual predictor on a double logarithmic scale. If the curves are parallel, then the PHA assumption is met. For the OP method, the observed function represents the Kaplan-Meier distribution, and the predicted function represents the baseline hazard of the Cox regression. If the two functions are close to each other, the PHA hypothesis is satisfied. If the PHA hypothesis fails to be satisfied for any of the predictors, the so-called stratified Cox model should be identified [221]. In the stratified Cox model for each of the predictors that does not satisfy the PHA, an individual baseline hazard function can be created. In sophisticated modelling, the statistical significance of the parameters should also be evaluated based on the analysis of their p-values, which provides the most informative information for the root-cause analysis of the performance losses of the changeovers and setup process, as it highlights which variables influence the related activity times significantly.

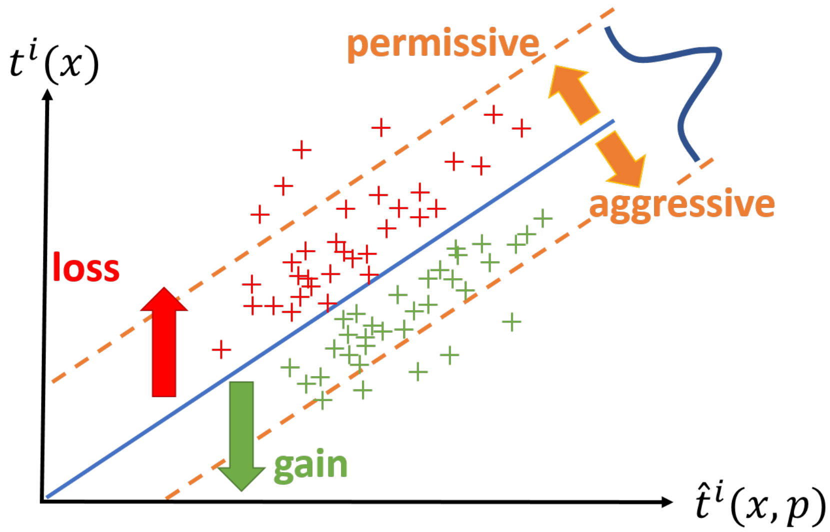

FIGURE 4.5: The targeting model compares the measured $t^i(\mathbf{x})$ and the estimated activity times $\hat{t}^i(\mathbf{x}, p)$.

The details of these statistical tests and their applicability to root-cause analysis will be presented in the case study.

4.2.3 Targeting model-based performance monitoring

The $\hat{t}^i = S^{-1}(\mathbf{x}_k, p) = \hat{t}^i(\mathbf{x}_k, p)$ inverse of the survival function can be used to estimate if the i-th type of activity will be finished with a given probability, e.g., when $p = 0.5$, the model estimates the median of the activity times when the changeover is represented by the $\mathbf{x}_k$ feature vector. As Figure 4.5 shows, this model can be used as a dynamic targeting model that considers all the relevant aspects of the changeover represented by the $\mathbf{x}_k$ feature vector and allows the tuning of the expectations by the selection of the p probability of the finishing of the activities.

Based on the targeting model and the $t^i(\mathbf{x}_k)$ measured activity times, the $L^i(p)$ performance loss can be calculated

$$L^i(p) = \sum_{k=1}^{N} max(t^i(\mathbf{x}_k) - \hat{t}^i(\mathbf{x}_k, p), 0) \tag{4.4}$$

where N represents the number of observations. When the operators finish the steup and changeover activities sooner than expected, the gained time can also be quantified by the proposed gain $G^i(p)$ function:

$$G^i(p) = \sum_{k=1}^{N} max(\hat{t}^i(\mathbf{x}_k, p) - t^i(\mathbf{x}_k)), 0) \qquad (4.5)$$

A performance index can also be defined as the ratio of the measured and expected activity times, which can be considered as an overall operator efficiency indicator. The proposed measures can be aggregated to evaluate the work operators, machines or other aspects of the production process, as will be presented in the following application example.

4.3 Application example

The applicability of the proposed methodology is demonstrated in the development of a multi-product crimping production line. Due to our confidentiality agreement, the data were re-scaled and anonymized. This section is structured as follows. Section 4.3.1 describes the studied wire-harness production technology and the analyzed log file. Section 4.3.2 describes the results of the Cox regression, while the application of the models in performance monitoring is presented in Section 4.3.3.

4.3.1 Changeovers in crimping machines

The studied production line consists of several fully automated crimping machines that can cut, strip and terminate wires (see Figure 4.6).

As changeovers consider changes in wire spools, crimping tools and terminals, many types of changeovers can be detected, e.g.,

- only wire change: the operator needs to change only the wire and perform the learning process
- tool change: when the wire cross or terminal type (or both) is also changed
- terminal change: some terminals can be produced in the same tool, whereas others need a different tool

FIGURE 4.6: The studied automatic crimping machines log all the states and both setup and changeover activities.

The process steps are logged, and the log file stores the states of the machine (see Table 4.4).

All the integrated data are stored in a database structured as described in Table 4.1. The variables represent the number of length and cross-section area (CSA) changes, therein described by binary values (1 if there is a change). A wire change is also represented by a binary value. The number of tool changes can be 0, 1 or 2 based on how many tool changes are necessary. The number of terminal changes can also be 0, 1 or 2.

4.3.2 Results of the Cox regression analysis

First, the distribution of the time demand of the whole changeover process is analyzed. The impact of the studied variables has been checked by the sensitivity analysis shown in Figure 4.7. As this figure shows, the curve related to the cross-section change ($CSAChange$) deviates the most from the baseline, which indicates that this variable has the most significant influence on the time demand of the changeover.

The first row (Overall process) of Table 4.5 summarizes the parameters of the identified Cox model. When a parameter is smaller than the related variable, the changeover time increases. The analysis highlights that $OperatorSeniority$ does not affect the time demand of the changeover process, while $CSAChange$ is

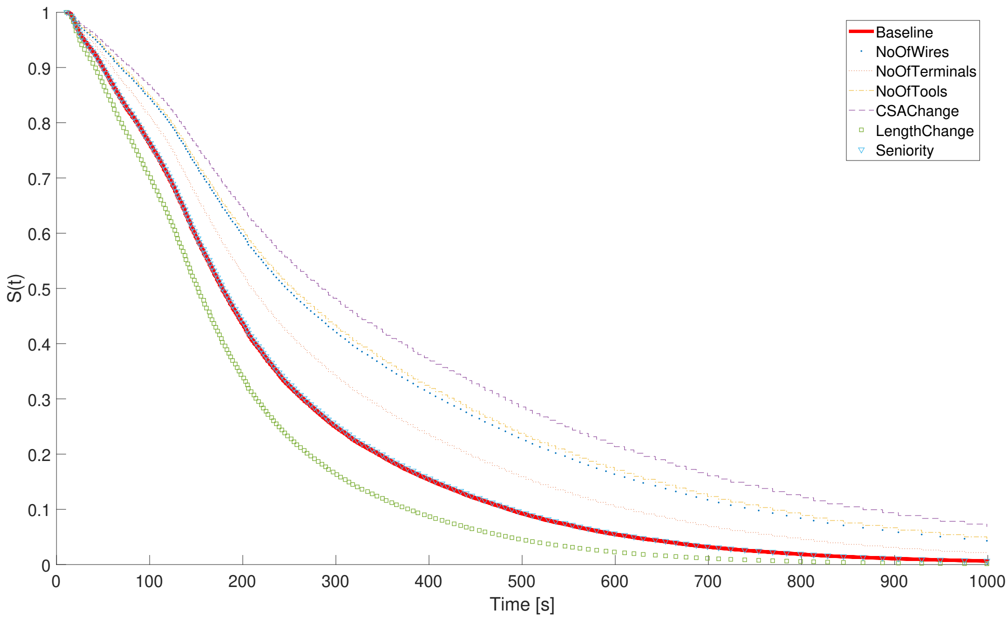

Figure 4.7: Survival functions of the whole process and the influences of the variables.

the most significant feature. The $No.ofTools$ and $No.ofWires$ variables have a considerable influence on the times. Note that these variables are not independent, and both $No.ofTools$ and $CSAChange$ change when the tools are changed.

The estimated uncertainty parameters are summarized in Table 4.6, while the p values are shown in the first row in Table 4.7, also confirming that $OperatorSeniority$ does not significantly influence the time demand of the process.

A changeover is decomposed into different states to further explore the root causes of the losses. Figure 4.8 shows the four studied steps of the process: the setup-changeover, setup-sample, setup-short fault, and setup learning steps.

Figure 4.8 a) presents the time demand of the Setup-Changeover step. Based on the Cox parameters (shown in the second row of Table 4.5), the $NoOfWires$ has the most significant influence on the time, and the curves showing the sensitivity of the $CSAChange$ and $NoOfTools$ variables also significantly deviate from the baseline.

The results of the Cox regression of the setup-sample process step can be seen in Figure 4.8 b). The parameters are given in the third row of Table 4.5. Note that $NoOfWires$ decreases the activity time because, during the setup-changeover step, the wire spool is replaced, and there are more preparation activities than there would be otherwise.

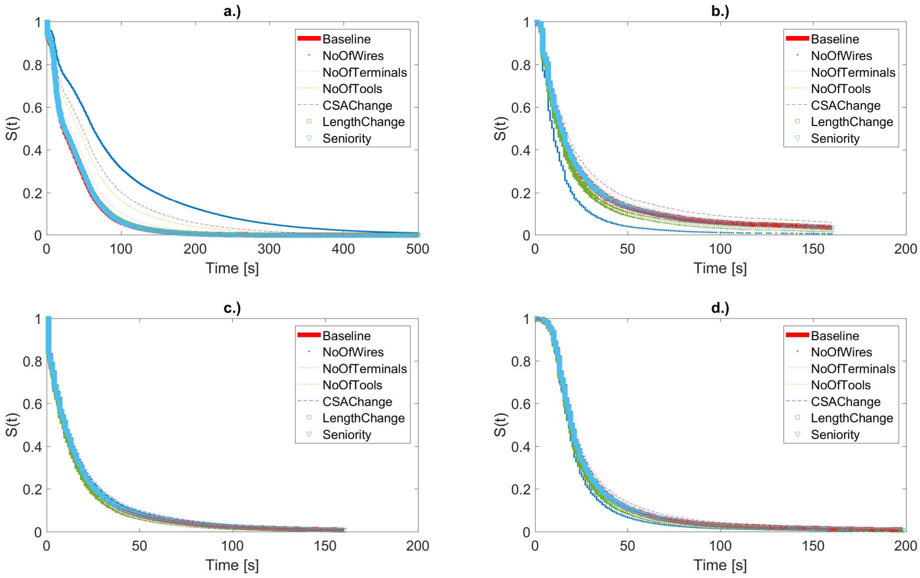

FIGURE 4.8: a.) Setup-Changeover b.) Setup-Sample c.) Setup-Short Fault d.) Setup-Learning. This figure shows the survival functions of individual machine states.

Figure 4.8 c) shows the result of the setup-short fault step. The Cox parameters are not statistically significant in this case (see the fourth row in Table 4.5), and the parameters are close to zero, which correctly reflects that this process step occurs randomly.

The Cox parameters of the setup-learning step are shown in Figure 4.8 d. The small parameter values shown in the last row in Table 4.5 reflect a well-controlled process. The change in cross-section increases the activity time, which is entirely in line with the experience of the process engineers.

The application of the method assumes that the proportional hazard assumption (PHA) is satisfied for each predictor. As presented in the previous section, when the Schoenfeld residuals are correlated and the rank order of the survival times are not correlated, then the PHA is satisfied for the studied predictor. As the correlation values in Table 4.8 show, the PHA assumption is not satisfied in the case of the total activity time for the $NoOfWires$, $NoOfTerminals$ and $NoOfTools$ variables; in the case of the setup-changeover, the $NoOfWires$ variable should be modelled by stratified Cox regression.

A graphical validation of the PHA has also been performed. There are two graphical methods. One method is the log-log method. The Kaplan-Meier curves for

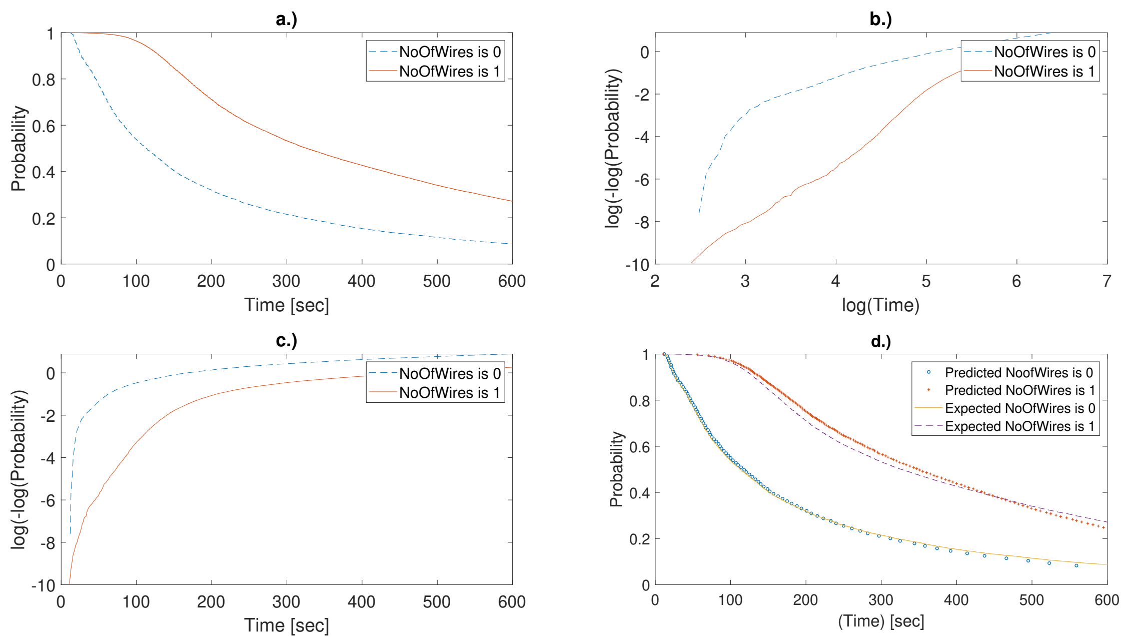

FIGURE 4.9: a.) Kaplan-Meier distribution of marked events b.) Graphical checking of the PHA being satisfied in log-log scale c.) Graphical checking of the PHA being satisfied in log scale d.) Predicted vs expected examination of satisfying the PHA.

each value of the predictors must be twice logarithmized, and the proportional hazard analysis is satisfied if these curves are parallel [218]. The functions of $NoOfWires$ of the data are plotted in Figure 4.9 b),c). Figure 4.9 b) has the abscissa label also logarithmized. The other method is the predicted vs expected method. The Kaplan-Meier curve and the baseline curve of the Cox regression need to be compared. If the curves are close to each other, the PHA assumption is satisfied [218]. These functions are displayed in Figure 4.9 d). The application of both methods leads to the previous conclusion, as the PHA is not satisfied for the $NoOfWires$ variable; thus, the stratified Cox model should be applied for modeling the overall process and the setup-changeover process step.

As Figure 4.10 and Table 4.10 show, this model describes the Setup-changeover process step well, while the overall process should be modelled when both $NoOfWires$ and $NoOfTools$ are used to form separate groups in the survival analysis. As Figure 4.10 and Figure 4.11 illustrate, these models show realistic results, and the effects of $CSAChange$ and $NoOfTerminals$ are in line with expectations.

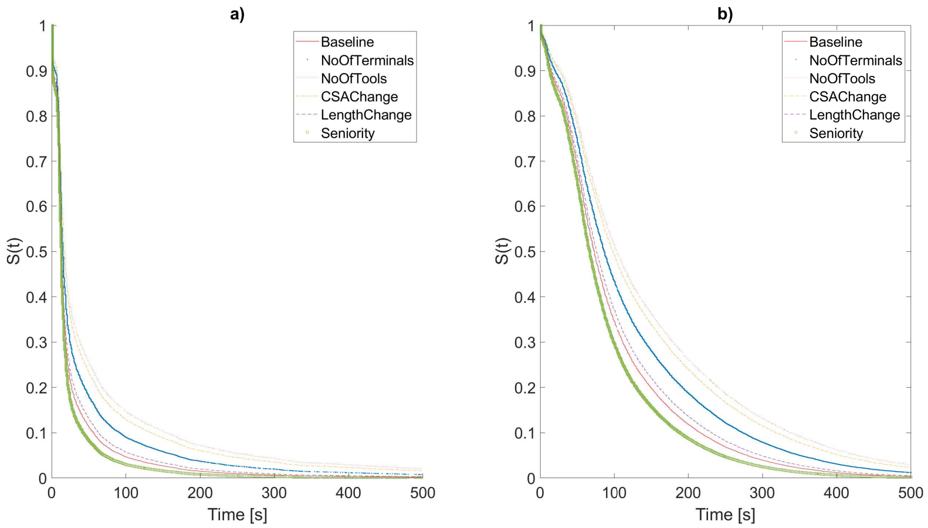

FIGURE 4.10: Stratified Cox model for setup-changeover. a) No. of Wires is 0;b) No. of Wires is 1.

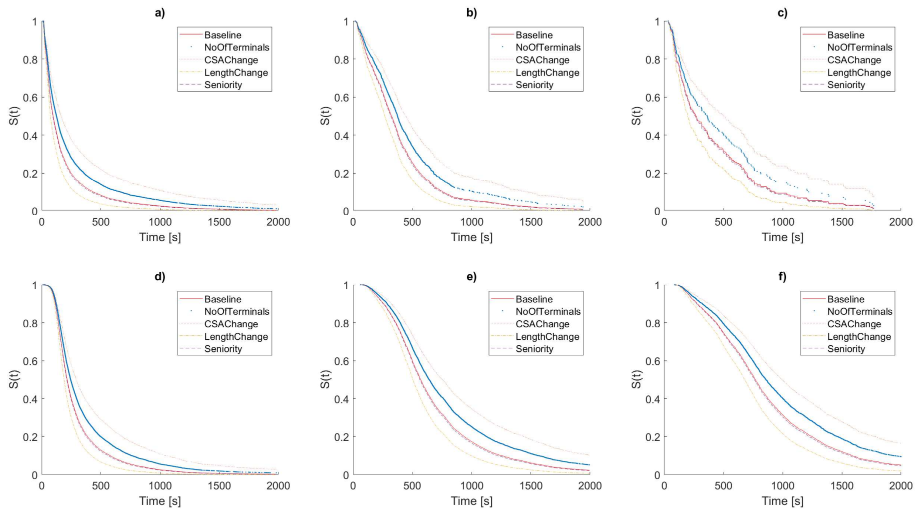

FIGURE 4.11: Stratified Cox model for the whole process. a) No. of Wires is 0, No. of Tools is 0; b) No. of Wires is 0, No. of Tools is 1; c) No. of Wires is 0, No. of Tools is 2; d) No. of Wires is 1, No. of Tools is 0; e) No. of Wires is 1, No. of Tools is 1; f) No. of Wires is 1, No. of Tools is 2.

TABLE 4.1: Integrated information database and the key variables

Database	Variable	Range	Description
Machine log-data	Time stamp [$datetime$]	[$-$]	The start time stamp of the status
	Event name [$-$]	[$Setup - Changeover, Setup - Sample, Setup - ShortFault, Setup - Learning, NoCause$]	Name of the actual status of machine
	Order ID [$-$]	[$-$]	The ID of the order
	Operator ID [$-$]	[$-$]	The ID of the operator
	Machine name [$-$]	[$-$]	The ID of the machine
	Duration [s]	[$1-$]	The duration of actual status
	Number of Wires [pcs]	[$0, 1$]	If the wire is changed, then it is 1 and 0 otherwise.
	Number of Terminals [pcs]	[$0, 1, 2$]	If the terminal is changed, then it is 1 or 2 and 0 otherwise.
	Number of Tools [pcs]	[$0, 1, 2$]	If the tool is changed, then it is 1 or 2 and 0 otherwise.
	Number of CSA [pcs]	[$0, 1$]	If the cross section of wire is changed, then it is 1 and 0 otherwise.
	Number of Length [pcs]	[$0, 1$]	If the length of wire is changed, then it is 1 and 0 otherwise.
Order descriptions	Order ID [$-$]	[$-$]	The identification of produced order
	CSA [mm^2]	[$0.13 - 35$]	Wire cross section
	Length [mm]	[$30 - 8514$]	Length of the wire
	Type of terminal [$-$]	[$-$]	Type of the terminal
	Type of wire [$-$]	[$-$]	Type of the wire
Operator data	Operator ID [$-$]	[$-$]	Operator IDs
	Seniority [$weeks$]	[$0-$]	Seniority of the operator (number of weeks working at the company)

TABLE 4.2: Description of branches

Event	Code	Next event	Description
Setup-Changeover	A	Setup-Sample	Normal sequence
Setup-Changeover	A	Setup-Short Fault	If only cutting occurs (no terminating)
Setup-Changeover	A	Setup-Learning	When only the length of wire is changed
Setup-Sample	-	-	-
Setup-Short Fault	B	Setup-Learning	Normal sequence
Setup-Short Fault	B	Production	If no need for more learning
Setup-Learning	-	-	-

TABLE 4.3: Input variables of the Cox regression model

CaseID	Duration	Censored	Features representing the changeover				
1	t_1	s_1	$x_{1,1}$	$x_{1,2}$	.	.	$x_{1,m}$
2	t_2	s_2	$x_{2,1}$	$x_{2,2}$	.	.	$x_{2,m}$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
8	t_8	s_8	$x_{8,1}$	$x_{8,2}$	.	.	$x_{8,m}$
9	t_9	s_9	$x_{9,1}$	$x_{9,2}$	.	.	$x_{9,m}$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
N	t_N	s_N	$x_{N,1}$	$x_{N,2}$	.	.	$x_{N,n}$

TABLE 4.4: Logged machine states

Status	Description
Production	Logged when the actual production is started
Production end	Logged at the end of the order (all batches are done)
Production-Short fault	Micro-stoppages between two batches or during a fault
Setup-Changeover	Logged when the changeover is started
Setup-Learning	Logged at the beginning of the learning (measurement, tool/machine setup)
Setup-Sample	Logged when the actual sample production is started
Setup-Short Fault	Micro-stoppages during changeovers
No Cause	Starts when the downtime is longer than 30 second and the operator did not log any cause.

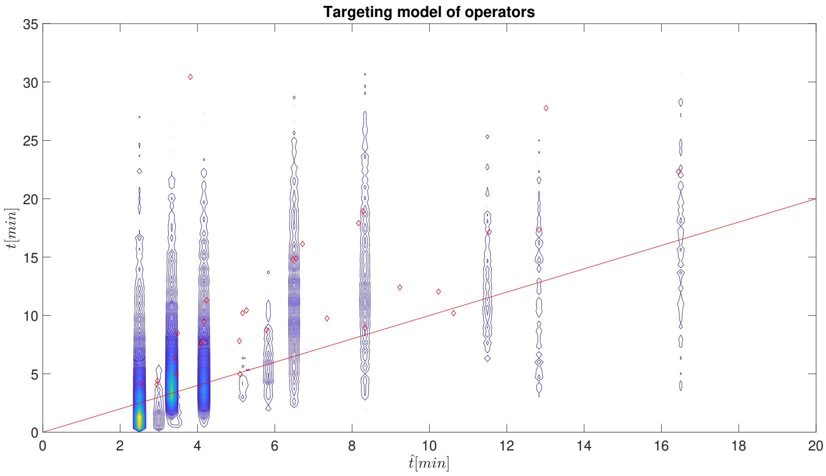

FIGURE 4.12: Scatter plot of the prediction of the targeting model ($\hat{t}$, $p = 50\%$) and the measured (t) activity times. The red diamonds represent the average measured activity times of identical changeovers.

4.3.3 Application to performance monitoring

This section aims to present how the resulting models can be used to evaluate the efficiency of the operators based on the methods presented in Section 4.2.3.

Figure 4.12 shows the targeting model of the operators, where the nominal ($\hat{t}$) and measured (t) times are compared. Every column represents a typical changeover, while the red diamonds represent the average of the related activity times. This figure nicely demonstrates the asymmetric distribution of delays/performance losses.

The operator performance can be evaluated by using the proposed gain and loss model. Based on the models, the performance losses for each operator, machine, and shift can be determined. The performances of a productive vs. less-productive operator are depicted in Figure 4.13 and Figure 4.14. These time-variant performances can be averaged, and the total loss or gain can be aggregated to other attributes (e.g., machine). Figure 4.15 shows the results of such an analysis. As this heatmap shows, at machine 27, operator 98 works well, whereas operators No. 44 and No. 16 are performing below expectations. It can also be seen that operator 98 performs well with every machine, whereas operator 145 performs significantly poorly with all machines. The detailed analysis highlights that operator 145 is a new employee, has worked on many different machines, and has not had a chance to learn correctly on either machine, information that is useful for the shift supervisor.

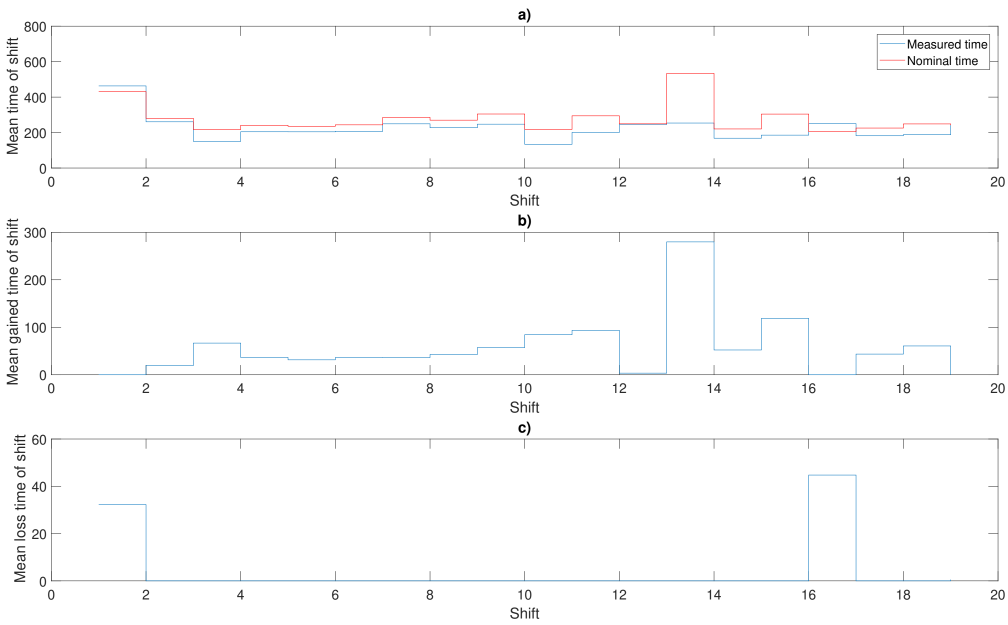

FIGURE 4.13: The performance of one of the best operators. The average shift measured and nominal times are shown in diagram a). Subfigure b) shows the high gained times, while c) shows the rare loss times.

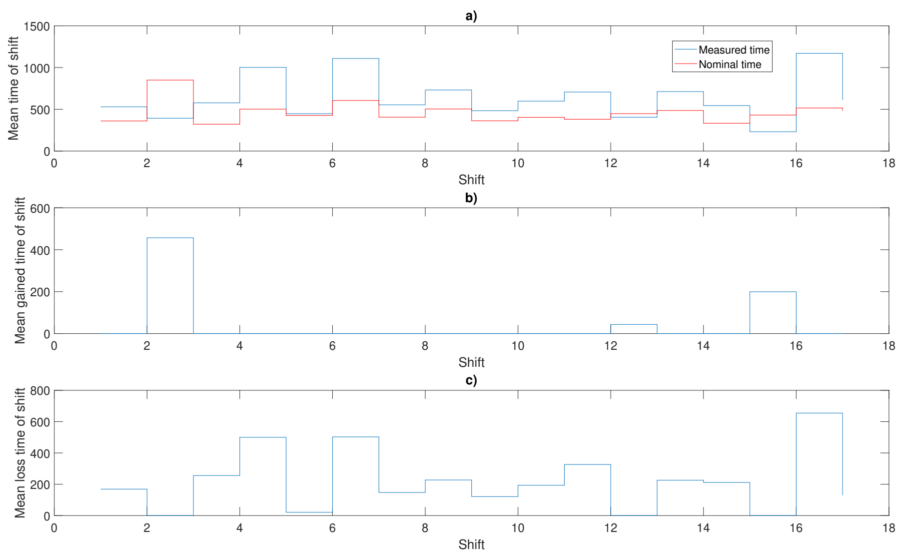

FIGURE 4.14: The performance of one of the less-efficient operators. The average shift measured and nominal times are shown in plot a). The rare gained times of one shift over shifts are plotted in diagram b), while the significant loss times are in c).

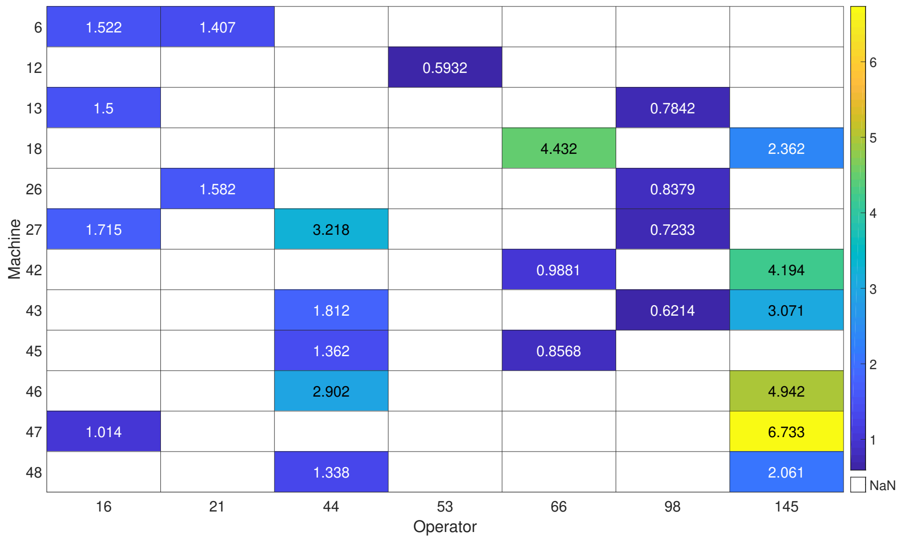

FIGURE 4.15: The calculated efficiencies of different operators working with machines. The operator performs better than the expected changeover time if the value is less than 1. We can note that operator $No.145$ is the worst with all machines except for machine $No.18$.

4.4 Details of the Cox regression

The Chapter presents the detailed results of the Cox regression. Table 4.5 shows the identified parameters, while Tables 4.6 and 4.7 show their standard errors and p-values. The PHA is examined using the Schoenfeld residuals in Table 4.8. The parameters of the stratified Cox model are shown in Table 4.9 and Table 4.10.

TABLE 4.5: The b parameters of Cox regression. The activities are slower if the parameter is negative at this changing feature. The higher the absolute value of the number, the more significant the difference.

	No. of Wires	No. of Terminals	No. of Tools	CSA Change	Length Change	Operator Seniority
Overallproces	−0.4726	−0.2494	−0.4957	−0.6314	0.2646	−0.0001
Setup-Changeover	−0.8760	−0.1995	−0.4260	−0.5530	−0.0197	0.0016
Setup-Sample	0.4642	0.0051	−0.0726	−0.1591	0.1370	0.0035
Setup-Short Fault	−0.0617	−0.0151	−0.1001	−0.0973	0.0743	0.0006
Setup-Learning	0.1997	0.0219	−0.0502	−0.1085	0.0817	0.0026

TABLE 4.6: Standard errors of coefficient estimates (b).

	No. of Wires	No. of Terminals	No. of Tools	CSA Change	Length Change	Operator Seniority
Overallprocess	0.0135	0.0312	0.0311	0.0242	0.0145	0.0002
Setup-Changeover	0.0130	0.0267	0.0267	0.0209	0.0131	0.0002
Setup-Sample	0.0128	0.0192	0.0191	0.0131	0.0092	0.0002
Setup-Short Fault	0.0080	0.0121	0.0120	0.0082	0.0060	0.0001
Setup-Learning	0.0111	0.0171	0.0170	0.0110	0.0090	0.0001

TABLE 4.7: The p values of the data. If the p value is less than 0.05, then the data are significant.

	No. of Wires	No. of Terminals	No. of Tools	CSA Change	Length Change	Operator Seniority
Overallprocess	0.0000	0.0000	0.0000	0.0000	0.0000	0.6268
Setup-Changeover	0.0000	0.0000	0.0000	0.0000	0.1326	0.0000
Setup-Sample	0.0000	0.7926	0.0001	0.0000	0.0000	0.0000
Setup-Short Fault	0.0000	0.2117	0.0000	0.0000	0.0000	0.0000
Setup-Learning	0.0000	0.2017	0.0032	0.0000	0.0000	0.0000

TABLE 4.8: Validation of the PHA based on the examination of the Schoenfeld residuals. The PHA is satisfied if the time-ranked variables and the Schoenfeld residuals are not correlated with each other.

	No. of Wires	No. of Terminals	No. of Tools	CSA Change	Length Change	Operator Seniority
Overallprocess	0.4031	0.2768	0.2820	0.1170	−0.1006	0.0066
Setup-Changeover	0.3736	0.0622	0.0698	0.0159	−0.0173	−0.0146
Setup-Sample	−0.0906	0.0216	0.0244	0.0341	−0.0087	−0.0083
Setup-Short Fault	0.0460	−0.1148	−0.1161	−0.0420	0.0151	0.0243
Setup-Learning	0.0350	0.0429	0.0414	−0.0086	−0.0205	−0.0108

TABLE 4.9: Parameters of the stratified Cox model for the overall process

	No. of Terminals	CSA Change	Length Change	Operator Seniority
b parameters	−0.2391	−0.5028	0.2812	0.0003
Error of b	0.0307	0.0223	0.0141	0.0003
Significance	0.0000	0.0000	0.0000	0.2036
PH ass	0.0364	0.0735	0.0231	0.0247

Table 4.10: Parameters of the stratified Cox model for setup changeover

	No. of Tools	No. of Terminals	CSA Change	Length Change	Operator Seniority
b parameters	−0.2416	−0.4661	−0.4021	−0.0679	0.0017
Error of b	0.0278	0.0279	0.0211	0.0133	0.0002
Significance	0.0000	0.0000	0.0000	0.0000	0.0000
PH ass	−0.0186	−0.0136	0.0189	0.0811	−0.0219

4.5 Conclusion of reducing machine setup and changeover times by survival analysis

This Chapter highlighted that survival analysis can be used to model the activity times of machine setups and changeovers. Based on the statistical analysis of the model parameters, the main drivers of the performance losses can be identified. The developed model considers the stochastic nature of complex processes and the work of operators. Based on the inverse of the cumulative distribution function of the activity times, a dynamic targeting model can be developed. The model can be tuned to express the expectations of the process engineers, and the calculated performances can be aggregated to evaluate operator and machine efficiencies. The presented application example highlights how the model assumptions can be validated and what type of information can be extracted based on the analysis of the model.

Chapter 5

Fuzzy activity time-based model predictive control

The sequencing and line balancing of manual mixed-model assembly lines are challenging tasks due to the complexity and uncertainty of operator activities. The control of cycle time and the sequencing of production can mitigate the losses due to non-optimal line balancing in the case of open-station production where the operators can work ahead of schedule and try to reduce their backlog. The objective of this Chapter is to provide a cycle time control algorithm that can improve the efficiency of assembly lines in such situations based on a specially mixed sequencing strategy. To handle the uncertainty of activity times, a fuzzy model-based solution has been developed. As the production process is modular, the fuzzy sets represent the uncertainty of the elementary activity times related to the processing of the modules. The optimistic and pessimistic estimates of the completion of activity times extracted from the fuzzy model are incorporated into a model predictive control algorithm to ensure the constrained optimization of the cycle time. The applicability of the proposed method is demonstrated based on a wire-harness manufacturing process with a paced conveyor, but the proposed algorithm can handle continuous conveyors as well. The results confirm that the application of the proposed algorithm is widely applicable in cases where a production line of a supply chain is not well balanced and the activity times are uncertain.

Industry 4.0- and IIoT-based production management systems explicitly aim to connect decentralized production units and information sources to increase productivity and flexibility. Besides the various factors that affects the variability of production lines [222], as human resources are still utilized in many manufacturing systems, the development of these processes should also focus on the performance of the operators. Due to the complexity and uncertainty of human behavior, balancing and scheduling the work of the operators are challenging tasks [223]. As the activity times depend on the complexity of the products, balancing of mixed-model assembly lines (MMALs) with high product variety, is of outstanding complexity [25]. The incorporation of the stochastic behavior of human nature into such an uncertain optimization problem is a significant improvement compared to the deterministic models [224]. Therefore, accurate activity-time monitoring and the construction of activity-time models, is of crucial importance [207].

Modular assembly lines with manual workstations have already been analyzed for different types of conveyors [225]. In closed-station production, the operator must stop the conveyor even in the event of a minor delay [174]. Our research focuses on open-stations where the operators can work ahead of schedule or can be delayed [173], and the production only stops when the delay exceeds a critical limit. These open workstations reduce the capacity loss by decreasing the risk of stopping the conveyor, but the modeling and optimization of these processes are much more challenging as the model has to handle idle and delay times [226]. The most sophisticated model of open-stations is based on worker movement analysis that recognizes the interactions between operators and analyzes idle times as well as the risk of stopping production in the event of unmanageable backlogs [227]. Although this model is excellent for detailed analysis, unfortunately it is too complex to handle multiple modular products.

As the objective of the Chapter is to solve this problem, in Section 5.2, a state-space model for the efficient modeling of the flow of the assembly line and estimation of the activity times for every station is proposed. The model-based integration of the isolated production cells facilitates the model-based control of the production flow. Even in the case of open-station production lines, the efficiency of the processes significantly depends on the cycle time. Recently, the IIoT-based infrastructural background of an algorithm that continuously sets the cycle time to maximize the productivity whilst preventing the conveyor line from being stopped [228] and a method capable of estimating the elementary activity times that can serve as parameters in the proposed state-space model were developed [207].

The developed state-space model (proposed in Section 5.2) can also be utilised in digital twins. Usually, the digital twin model is based on discrete-event simulators (DES). Although these tools support stochastic simulators, their model cannot be directly utilised in control algorithms. The key benefit of the developed state-space model-based predictive control (MPC) algorithm is that the related model can be easily implemented in every platform, so the model can be easily applied in digital twins. This interoperability-based double utilisation is crucially important as it allows the consistent development and maintenance of the models.

Many manufacturing processes cannot be fully automated, so human operators are working at the assembly workstations. The stochastic nature of operators causes an essential problem in cycle time optimisation, line balancing and scheduling [229, 230]. In order to handle this problem, in this work a fuzzy set-based activity time representation is proposed. The primary role of the fuzzy sets is to represent the uncertainty of the knowledge about the activity times. This representation is beneficial as when the work of the operators is statistically consistent, and the historical data is available for the characterisation of the distribution of activity times, the fuzzy sets can approximate the related distribution functions. On the other hand, when there are frequent changes in the process, or the production of a new product begins, the data-driven information can be complemented by the a priori expert knowledge of the process engineers and operators (see Section 5.3) and thus the growing trend of greater variety of products [231] can be handled.

Fuzzy time distributions can be conveniently applied for the estimation of the time of certain tasks [232] and activity times can be represented by triangular fuzzy numbers [233]. Moreover, fuzzy time distributions can be applied for the calculation of task times [234] and project time and cost [235] in project management. The applicability of fuzzy activity times has already been demonstrated in the case of fuzzy line-balancing approaches [236] for the improvement of production line performance using discrete event simulations [237] and for machine scheduling with fuzzy processing times [238].

To efficiently handle the asymmetric distribution of human performance, in Section 5.3, the importance of the application of LR (left-right) fuzzy sets [239] for the representation of operator activity times is highlighted. The application of fuzzy sets is beneficial as it facilitates the integration of measured activity times and takes into consideration the knowledge of process experts and engineers [240], which also makes the proposed method highly applicable with regard to the preliminary design of processes.

The modeling of assembly lines is important as the models are the cornerstones that optimize the operation. Just to mention the few of the latest publications, a new mixed-integer linear programming formulation was proposed to optimize the steady state of these lines [241] and a control policy was derived by using a simulation-based optimization approach that offers a powerful technique to control the considered system [242]. Although, as it is highlighted by the above examples, the optimization of the cycle time is mainly studied as part of a line-balancing problem as the continuous optimization and control of the cycle time can significantly improve the performance of complex processes. Successful applications of this concept have already been reported, e.g., particle swarm optimization has been used to simultaneously minimize the cycle time and total energy consumption [243], moreover, a multi-objective metaheuristic algorithm [244] simultaneously minimized the wastage at each station and the work overload.

To ensure flexibility and handle the time-varying nature of the process, in Section 5.4, an approach that seeks to determine an optimal solution under a prediction horizon is proposed. Thus, it is formalized as a model predictive control (MPC) problem.

The application of an MPC-based control framework has the advantage of effectively optimizing the production under a defined time horizon even in the presence of uncertainty, forecast errors and different types of operational constraints, e.g., capacity, inventory, control variable [245]. MPC has several successful applications in the case of discrete event systems, e.g., it has already been applied for the minimization of the overall waiting time and energy consumption of a baggage handling system [246] and the optimal control of a multi-product, multi-echelon supply chain [247]. The most similar formalization to our approach is presented in the work of De Schutter and van den Boom [248], where the system is characterized as a linear discrete event system and formulated as a state-space model, accordingly.

This Chapter proposes an MPC-based cycle time control algorithm for open-station conveyor lines when the production sequencing is determined by the requirements of JIT (just-in-time) production. Although the applicability of the proposed method is demonstrated on a paced conveyor, the developed MPC can also control the speed of unpaced production lines. The results will illustrate that the dynamically optimized setting of the cycle time can improve the utilisation of not perfectly balanced workstations.

5.1 Overview of model-based control of operator activity

This Chapter aims to develop a cycle time control algorithm for conveyor-based production lines that are frequently used in JIT (just-in-time) production manufacturing processes. The main requirement of the control algorithm is that it should effectively handle the stochastic nature of the operators' assembly times.

As MPC usually requires a simple model that can be optimized at any instant of time, the integration of fuzzy models into this scheme is far from a trivial task. The most widely applied method is based on the extraction of linear models [249]. Another approach of fuzzy predictive control when fuzzy multicriteria decision-making is integrated into the MPC using fuzzy sets is to translate the goals and constraints in a transparent way [250]. In this work, a third novel approach is proposed. The α-cuts of the fuzzy sets are extracted and the estimated lower and upper bounds of the activity times used to formalize the constrained optimization problem that sets the cycle time of each cycle based on the estimated uncertainties of the activity times.

According to these, the Chapter is motivated by the problem of handling the uncertainty of activity times on open-station assembly lines and its main contributions are the following:

- a state-space model was developed to represent the flow of the modules of modular products (in Section 5.2),
- the fuzzy time distribution is used to handle the stochastic nature of operators and the uncertain a priori knowledge of the process engineers about the activity times,

- to handle the asymmetric distribution of human performance, the activity times are represented as the sets of left-right fuzzy numbers and their α-cut-based confidence values are used to determine optimistic and pessimistic estimates of the completion of activity times (in Section 5.3),
- a model-predictive control algorithm was developed to optimize the cycle time (in Section 5.4),
- the method can also be applied to control the speed of unpaced conveyors.

Evaluation of the effectiveness of the proposed control scheme follows these listed contributions in terms of the analysis of two use cases in Section 5.5 which serve as a proof of concept of the described method. The first is an illustrative production example which transparently demonstrates the proposed method. However, the second is motivated by an industrial wire-harness assembly line, due to confidentiality and aiming for reproducibility, simulations are applied in the case studies (such simulational investigations are well-accepted as it was highlighted in the literature overview, for example in [237]). The applied example is a well-documented production line which has already been applied to demonstrate how multilayer networks can be used in production flow analysis [251] and how soft sensors can be used to estimate activity times [207].

5.2 State-space model of modular assembly lines

As is shown in Figure 5.1, the studied assembly line consists of $w = 1, \ldots, N_w$ workstations where operators perform different sets of elementary activities related to the production of different types of modular products. The sequence of the N_p types of products is represented as $\pi(k) \in \{1, \ldots, N_p\}$ according to which type of product is started to be produced at the first workstation in the $k = 1, \ldots, N$-th cycle. The product types are defined based on their $m = 1 \ldots N_m$ modules according to the binary vectors $\mathbf{p}_p$, the product definition of which can be considered as the bill of materials (BOM) presented by a $\mathbf{P}$ matrix of $N_m \times N_p$ dimensions, where the columns represent which modules can be found in the $p = 1, \ldots, N_p$-th type of product. For example, assuming that only four types of modules are present, $\mathbf{p}_1 = [1, 0, 1, 1]^T$ represents that the first type of product

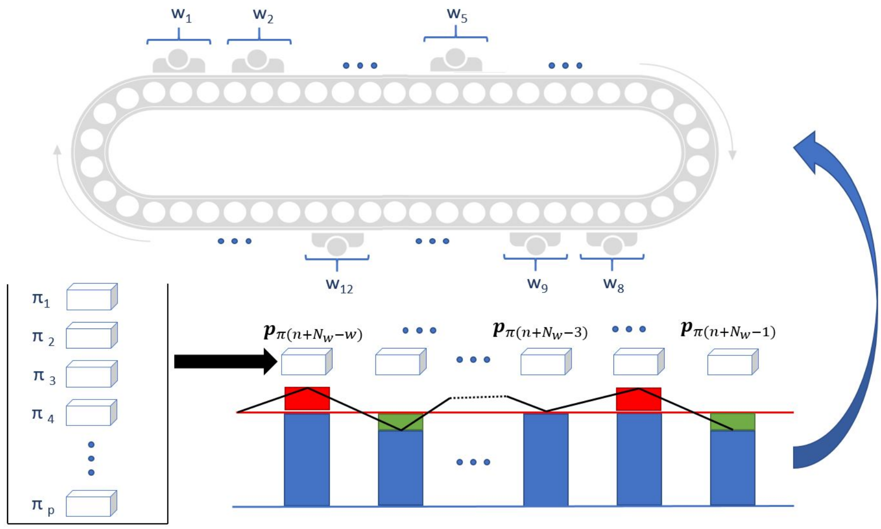

FIGURE 5.1: The cycle time setting problem of the open-station conveyor where every operator can be delayed or work ahead of schedule within certain limits for the production of a π sequence of different products.

consists of three modules (the second module is not installed in the first type of product) [251].

When $\mathbf{z}_f(k)$ represents the modules of the product that is started to be produced at the first workstation of the production line, namely $\mathbf{z}_f(k) = \mathbf{p}_{\pi(k-w)}$, the modules of the product produced at the w-th workstation is represented by a vector $\mathbf{x}_{f,w}(k)$ of length N_m and the set $\mathbf{x}_f(k) = [\mathbf{x}_{f,1}^T(k), \ldots, \mathbf{x}_{f,N_w}^T(k)]^T$ of these vectors defines the state of the workstation, the flow of the products can be represented by the state-space model in Eq. (5.1):

$$\mathbf{x}_f(k+1|k) = \mathbf{A}_f \mathbf{x}_f(k) + \mathbf{B}_f \mathbf{z}_f(k)\,, \tag{5.1}$$

where the matrix $\mathbf{A}_f$ as a shifted $N_m N_w \times N_m N_w$ identity matrix with the first N_m rows and last N_m columns of zeros defines the flow of the assembly line. Similarly, the first N_m rows of the matrix $N_m N_w \times N_m$. $\mathbf{B}_f$ form an identity matrix which represents how the production of the $\pi(k)$ type of product starts at the first workstation. Henceforth, the notation (k) after each mark denotes the measured value of the related metric at the beginning of cycle k, while $(k+j|k)$ represents the predicted value at the beginning of cycle k to the beginning of cycle $k+j$.

The following output equation can estimate the station times (activity times of the workstations) $\mathbf{t}_a(k+1|k) = [t_{a,1}(k+1|k), \dots, t_{a,N_w}(k+1|k)]^T$ at the workstations:

$$\mathbf{t}_a(k+1|k) = \mathbf{C}_f \mathbf{x}_f(k+1|k) \tag{5.2}$$

The matrix $\mathbf{C}_f$ of dimensions $N_w N_m \times N_w$ is defined in Eq. (5.3) based on the elementary activity times required for the production of the modules at the workstations based on the linear model $t_{a,w}(k+j|k) = \theta_w^T \mathbf{p}_p(k+j|k) = \theta_w^T \mathbf{p}_{\pi(k-w+i)}$ where θ_w represents the building blocks of the w^{th} rows of the matrix $\mathbf{C}_f$ with the elementary activity times related to implementing the modules into the product at the w^{th} workstation:

$$\mathbf{C}_f = \begin{bmatrix} \theta_1^T & 0 & \dots & 0 \\ 0 & \theta_2^T & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & & \dots & \theta_{N_w}^T \end{bmatrix} \tag{5.3}$$

The proposed model can be used to predict the station times for any workstations $t_{a,w}(k+j|k)$ during cycle k for any $j = 1, \dots, N-k$ step ahead of schedule. Due to the stochastic nature of human activities, these predicted station times will not be identical to the measured activity times denoted by $t_{a,w}(k)$.

The previously presented prediction model of activity times was developed for the formulation of a model predictive controller. However, to take into consideration the stochastic nature of human behaviour, how the activity times can be described by a fuzzy model and summed to form the $t_{a,w}(k+j|k)$ station time of each workstation at a predefined confidence level is presented in the following section.

5.3 Fuzzy representation of probabilistic activity times

To represent the uncertainty of the activity times, a fuzzy set-based method was proposed where the required time of the i^{th} activity is represented by the fuzzy variable A_i defined by the membership function $\mu_{A_i}(t)$. The main benefit of this approach is that it introduces the efficient integration of the data-driven information and expert knowledge of process engineers into the model [249].

Since the activity times are usually described by skewed distributions [224], their fuzzy values were defined by the well-known LR model [252] according to a univariate function that is quasi-concave over an interval I. The membership function μ defines a distribution of $\mu : I \rightarrow [0,1]$ and the subintervals I_1 and I_2 of I are such that μ monotonously increases over I_1 and monotonously decreases over I_2. Subsequently, I_1 is the left subinterval and I_2 the right subinterval of the domain of the membership function μ. If the maximum value is reached in more than one point, then a third central subinterval exists where μ is constant and maximal. If $I_1 = [a, b]$ and $I_2 = [c, d]$, then μ is defined as outlined in Eq. (5.4):

$$\mu(t) = \begin{cases} L\left(\frac{b-t}{b-a}\right) & \text{if } a \leq t \leq b \\ 1 & \text{if } b \leq t \leq c \\ R\left(\frac{t-c}{d-c}\right) & \text{if } c \leq t \leq d \\ 0 & \text{otherwise} \end{cases} \tag{5.4}$$

In Eq. (5.4), $L(x)$ and $R(x)$ ($L(x), R(x) : [0,1] \rightarrow [0,1]$) are non-increasing functions with the following two constraints: $L(0) = R(0) = 1$ and $L(1) = R(1) = 0$. When $L(y)$ and $R(y)$ are defined such that $y = 1 - x$, the resultant shapes are fuzzy trapezoid, which is sufficient in practice, as in probability theory it is of the uppermost importance to order the probability degrees according to the domain values where the function is interpreted rather than the precise assignment of probability degrees [253].

Based on our industrial experience and the analysis of the data taken from several production lines, $L(x) = \sqrt{max(0, 1 - x^2)}$ and $R(x) = \exp\left(-\|x\|^3\right)$ were selected as the LR fuzzy membership functions. A schematic example of the distribution of activity times and the fitted fuzzy distribution is presented in Figure 5.2, where

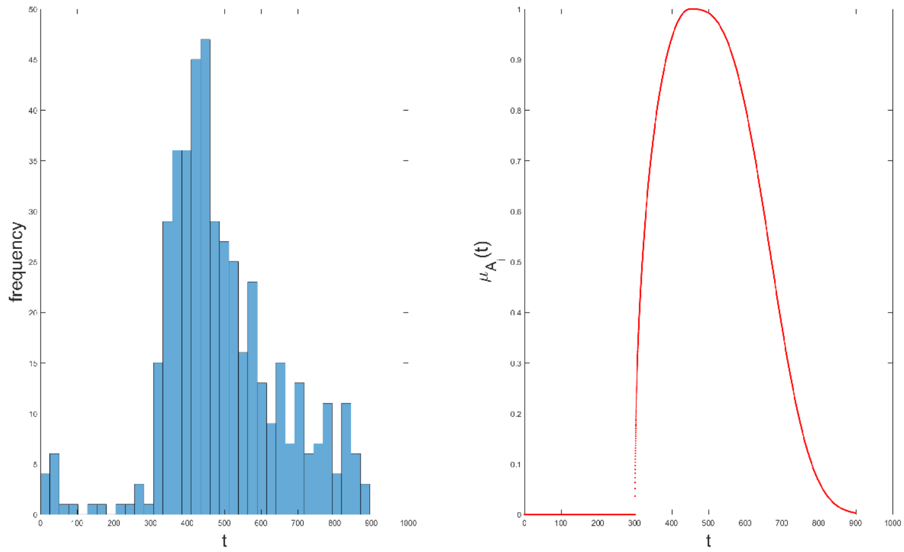

FIGURE 5.2: A schematic example of how the distribution of recorded activity times (left) can be approximated by LR fuzzy sets (right) with the identification of their parameters.

the fuzzy set is parametrised as $a = 150$, $b = c = 250$ and $d = 450$. As this example illustrates, the parameters of the fuzzy sets can easily be obtained by minimisation of the least-squares error between the membership values and the normalised histogram of the logged activity times. When historical data is unavailable, the fuzzy sets can be designed based on the expertise of the process engineers.

The support of μ_{A_i} is a time interval of τ at which the membership grade of $\mu_{A_i}(t)$ is greater than zero as presented by Eq. (5.5):

$$supp(A_i) = \{t | t \in \tau, \mu_{A_i}(t) > 0\} \tag{5.5}$$

Similarly, for $\alpha \in [0, 1]$ the α-cut of A_i is defined by Eq. (5.6) (in the case of $\alpha = 0$, the α-cut is equal to the support of μ_{A_i}):

$$[A_i]_\alpha = \{t | t \in \tau, \mu_{A_i}(t) > \alpha\} \tag{5.6}$$

This α-cut time interval can be considered to be a confidence interval, since it describes how short or long a given activity with a predefined confidence value is. As the activity times are represented by fuzzy sets, the optimistic/shortest expected activity time is $t_{i,L} = \min([A_i]_\alpha)$, while the pessimistic/longest expected activity time is $t_{i,R} = \max([A_i]_\alpha)$.

The addition and subtraction of two fuzzy values can be conducted according to Eqs. (5.7) and (5.8), respectively:

$$\mu_{A_i \oplus A_j}(z) = supp_{\{(x,y)/z=x+y\}} \min\left(\mu_{A_i}(x), \mu_{A_j}(y)\right) \tag{5.7}$$

$$\mu_{A_i \ominus A_j}(z) = supp_{\{(x,y)/z=x-y\}} \min\left(\mu_{A_i}(x), \mu_{A_j}(y)\right) \tag{5.8}$$

Subsequently, the level cuts of the sum of A_i and A_j can be defined according to Eq. (5.9):

$$[A_i + A_j]_\alpha = [A_i]_\alpha + [A_j]_\alpha = \{x + y | x \in [A_i]_\alpha, y \in [A_j]_\alpha\} \tag{5.9}$$

An example of how two fuzzy variables can be totaled based on their α-cuts is given in Fig. 5.3. The parameters of the fuzzy set denoted by dashed lines are $a_1 = 110$, $b_1 = c_1 = 50$ and $d_1 = 450$, while the parameters of the other fuzzy variables are $a_2 = 90$, $b_2 = c_2 = 40$ and $d_2 = 650$.

The proposed fuzzy set-based representation is highly beneficial as it represents the asymmetric uncertainty of the activities and with the aid of the α-cut values the fuzzy sets can be defuzzified as the left-hand side supreme of the fuzzy set, $t_{i,L} = \min([A_i]_\alpha)$ represents the shortest/optimistic time demand, while the pessimistic/longest expected time demand is represented by the right-hand side supreme of the set, $t_{i,R} = \max([A_i]_\alpha)$. The following section presents how this α-cut can estimate the earliest and latest station times in a modular production line in case of the stochastic nature of human operators and, thus, a general max-min problem can be formulated and incorporated into a model predictive control scheme.

5.4 Fuzzy activity time-based predictive control

The scheme of the developed framework is depicted in Figure 5.4. The main challenge of the studied modular multi-product production line is that the station times are uncertain and depend on which products, produced at a given station, are handled by the model predictive controller that utilises the state-space model presented in Section 5.2. The definitions of the sequenced modular products $\pi(k)$ are stored in the MES.

In the ideal case, there is a degree of freedom to optimize the sequence of the production by minimising the risk of conveyor stoppage and maximising the total utility/productivity of the production line. The proposed MPC has been developed for the same purpose, so it can maximise the benefits of the sequencing as it will be demonstrated in the case study (in Section 5.5) where the sequencing algorithm proposed in [254] was incorporated into the proposed framework.

Based on this information, the model calculates which elementary activities should be performed at a given station. As the activity times are represented by fuzzy sets, the optimistic/shortest expected activity time is the left-hand side supreme of the fuzzy set, $t_{i,L} = \min([A_i]_\alpha)$, while the pessimistic/longest expected activity time

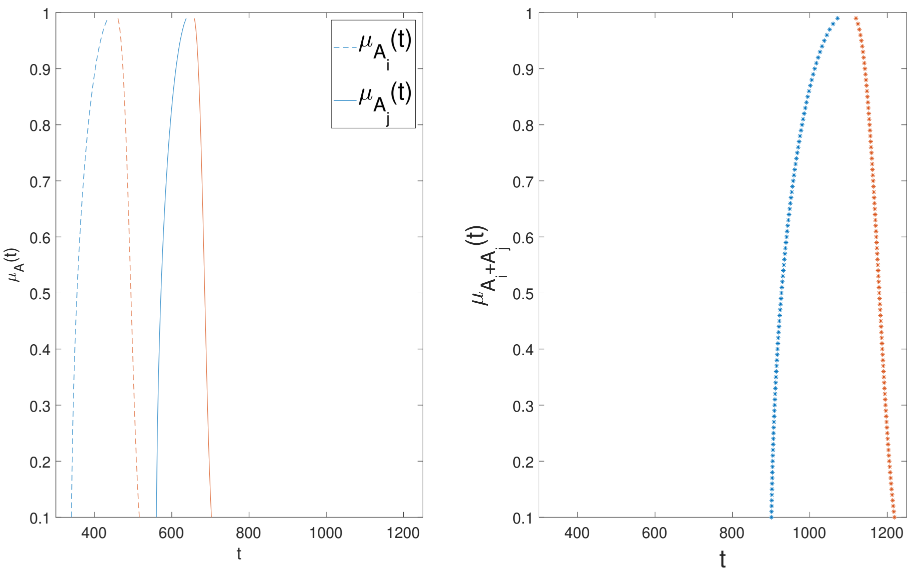

FIGURE 5.3: An example of how two fuzzy variables can be totaled based on their α-cuts. The parameters of the fuzzy set with dashed lines are $a_1 = 110$, $b_1 = c_1 = 50$ and $d_1 = 450$, while the parameters of the other fuzzy variables are $a_2 = 90$, $b_2 = c_2 = 40$ and $d_2 = 650$.

is the right-hand side supreme of the fuzzy set, $t_{i,R} = \max([A_i]_\alpha)$. Based on this concept, optimistic and pessimistic estimates of the activity times, $\mathbf{t}_{a,\{L,R\}}(k+j|k)$, finishing times, $\mathbf{t}_{f,\{L,R\}}(k+1|k)$, and the delays, $\mathbf{t}_{d,\{L,R\}}(k+1|k) = \mathbf{t}_{f,\{L,R\}}(k+1|k) - t_c(k+1)$, where $\mathbf{t}_{d,L}(k)$ is the lower and $\mathbf{t}_{d,R}(k)$ the upper bound of the duration of the delay at the start of the k^{th} cycle. (The $\{L,R\}$ notation in lowercase denotes the left, or right-hand supreme of the fuzzy sets). $t_c(k)$ is the sum of elapsed cycle times of the k^{th} cycle. According to this definition, this value is positive during delays and negative when the operators work ahead of schedule. As is shown in Figure 5.4, based on the extracted (defuzzified) activity times related to a given confidence (α-cut), the model predictive controller calculates the optimal cycle time as control signal, $u(k)$. The figure also illustrates that data collected concerning the elementary activity times can be used to update the parameters of the fuzzy sets based on the method that was presented in the previous section.

The following subsections will illustrate how the information extracted from the fuzzy activity-time models can be incorporated into model-based control schemes. As will be presented in the following subsection, when the control signal is calculated to prevent stoppage of the conveyor in the following cycle time, a one-step-ahead predictive controller is defined. Based on the constrained minimisation of the delay, in a prediction horizon H_p, a more sophisticated optimal control solution will also be proposed in the remaining part of this section.

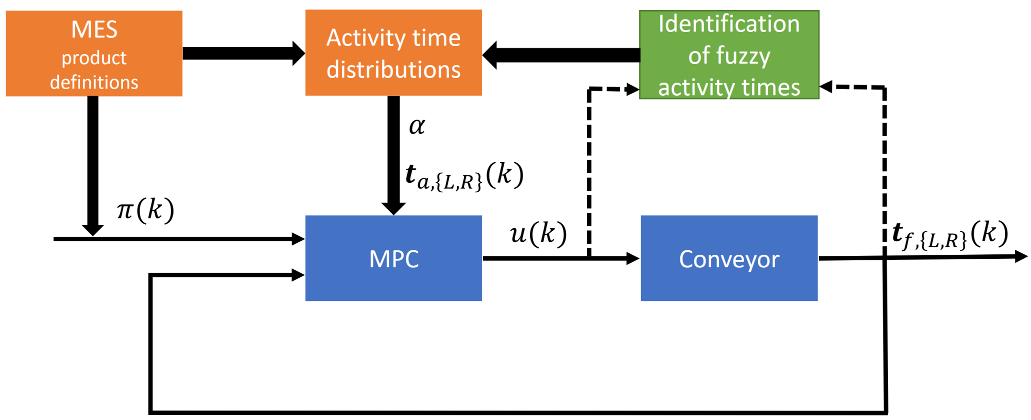

FIGURE 5.4: The scheme of the proposed fuzzy activity time-based model predictive controller (MPC). The fuzzy activity times are identified based on historical data collected from the conveyor. The models of the MPC are updated based on the sequence of the produced products.

5.4.1 One-step-ahead predictive control

Using the $\mathbf{t}_{a,\{L,R\}}(k+1|k)$ prediction of the lower or upper bound of the activity times (for a given α) at the beginning of the k-th cycle, the $\mathbf{t}_{f,L}(k+1|k)$ lower and $\mathbf{t}_{f,R}(k+1|k)$ upper boundaries of the completion times can be calculated. Based on the $t_c(k+1)$ start time of the $(k+1)^{th}$ cycle, the delay at every $(k+j)^{th}$ cycle can be predicted according to Eq.(5.10).

$$\mathbf{t}_{d,\{L,R\}}(k+1|k) = \mathbf{t}_{f,\{L,R\}}(k+1|k) - t_c(k+1) = \mathbf{t}_{f,\{L,R\}}(k+1|k) - (t_c(k) + u(k)) \tag{5.10}$$

where $u(k)$ denotes the cycle time set at the beginning of the k^{th} cycle. Therefore, the k^{th} cycle starts at $t_c(k)$ and finishes at $t_c(k+1) = t_c(k) + u(k)$.

The upper bound of the delay, $\mathbf{t}_{d,R}(k)$, cannot exceed a critical limit, therefore, a c_{crit} value can be defined which is equal to this critical limit or less than it. The cycle cannot be started should it be impossible to finish the tasks before this limit. Therefore, the criteria for not stopping the conveyor can be formulated as Eq. (5.11).

$$\max\left(\mathbf{t}_{f,R}(k+1|k)\right) - (t_c(k) + u(k)) < c_{crit} \tag{5.11}$$

where $\max\left(\mathbf{t}_{f,R}(k+1|k)\right)$ denotes the delay of the slowest operator (workstation).

By expanding the expression $(\mathbf{t}_{f,R}(k+1|k))$, the Eq. (5.12) can be derived.

$$\max\left((\mathbf{t}_{f,R}(k) + \mathbf{t}_{a,R}(k+1|k))\right) - (t_c(k) + u(k)) < c_{crit} \tag{5.12}$$

It should be noticed that $\mathbf{t}_{f,R}(k)$ is a measured value of the completion of the k^{th} cycle, while $\mathbf{t}_{a,R}(k+1|k)$ is a predicted one, therefore, making it possible to derive a one-step-ahead predictive controller.

The proposed algorithm continuously sets the cycle time $u(k)$ for every k^{th} cycle to avoid any stoppages, so the control signal/the cycle time should exceed the upper bound of the finishing time. The Eq. (5.13) shows how to $u(k)$ is defined.

$$\max(\mathbf{t}_{d,R}(k) + \mathbf{t}_{a,R}(k+1|k)) - c_{crit} < u(k) \tag{5.13}$$

The Eq. (5.14) shows that stoppages can be prevented by setting the $u(k)$ to ensure that the expected maximum delay should be less than $u(k)$.

$$u(k) = \max(\mathbf{t}_d(k) + \mathbf{t}_{a,R}(k+1|k)) - c_{crit} \tag{5.14}$$

If an unpaced conveyor is used during the production, the speed of the line can be defined as the output of the controller by using the $s(k) = \frac{l}{u(k)}$ transformation, where l stands for the length of the conveyor line.

5.4.2 Constrained fuzzy model predictive control

In addition to the one-step-ahead predictive control, a much more effective model predictive control scheme that minimizes the effect of tuning for horizon of longer duration, H_p, by determining a control sequence of length H_c $\mathbf{u}^*(k) = [u(k), u(k+1), \ldots, u(k+H_c)]$ where H_c denotes the control horizon was formulated.

As the control horizon cannot exceed the prediction horizon ($H_p \geq H_c$), it is assumed that the control variable remains constant after the control horizon has ended until the end of the prediction horizon $u(k+H_c+1), \ldots, u(k+H_p) = u(k+H_c)$.

In a similar manner to the cost functions of simple assembly line balancing problems [255], several types of cost functions can be defined, e.g., the cost function can be formalized to minimize the cycle time which in turn minimizes any delay to the expected finishing times in Eq. (5.15), which also optimizes the utilities of the operators and attempts to ensure a well-balanced workload.

$$\min_{\mathbf{u}^*(k)} \mathbf{u}^*(k)^T \mathbf{R} \mathbf{u}^*(k) \tag{5.15}$$

The type of model predictive control can primarily be determined from the definition of the control constraints as the formulation of the control sequence seeks to avoid stoppages to the conveyor belt due to the accumulation of a delay. The constraints that ensure this leads to the formulation of a quadratic optimisation problem in Eq. (5.16).

$$\mathbf{A}_R\mathbf{u}^*(k) < \mathbf{b}_R \tag{5.16}$$

where $\mathbf{A}_R$ denotes a lower triangular matrix and $\mathbf{b}_R = t_c(k) + c_{crit} - \mathbf{t}_{f,R}(k+j|k)$.

Therefore, the constraint applied to the cycle time should be rearranged in the form of Eq. (5.16). By rearranging Eq. (5.11):

$$\mathbf{t}_{f,R}(k+j|k) - t_c(k) - c_{crit} < \sum_{j=1}^{H_p} u(k+j-1) \tag{5.17}$$

$$-\sum_{i=j}^{H_p} u(k+j-1) < t_c(k) + c_{crit} - \mathbf{t}_{f,R}(k+j|k) \tag{5.18}$$

5.5 Examples of applications

Two examples of applications have been defined to demonstrate the applicability of the proposed fuzzy activity time-based approach. The first, an easily understandable example, is reproducible and transparent, while the second demonstrates the benefits of the model-based controller in more complex and realistic situations. However, the second example is motivated by an industrial wire-harness assembly line, due to confidentiality and aiming for reproducibility, simulations are applied in the second case study as well. Since multiple products with different work demand are produced, the production lines cannot be perfectly balanced. The application examples aim to demonstrate how the benefits of the sequences optimized based on the high/low product complexity strategy can be realized with the help of the proposed control algorithm.

5.5.1 Illustrative example

The $N_w = 5$ workstations of the studied illustrative assembly line produce $N = 500$ modular products during every shift in 10-piece batches of the same product type. The $N_m = 5$ modules determine the elementary activities that should be performed at each workstation. The nominal time values of these activities are presented in matrix θ, where each row represents a workstation and each column provides the activity time of the related module at the given station:

$$\theta = \begin{bmatrix} 250 & 40 & 25 & 70 & 30 \\ 260 & 35 & 0 & 100 & 20 \\ 230 & 10 & 80 & 80 & 15 \\ 240 & 32 & 58 & 85 & 0 \\ 260 & 23 & 0 & 72 & 60 \end{bmatrix} \tag{5.19}$$

The matrix $\mathbf{P}$ ($N_p \times N_m$) matrix defines the types of products, where the rows denote the type of products and the columns the modules. The nominal values $\mathbf{t}_a$ of the station times can be calculated as $\mathbf{t}_a = \theta^T \mathbf{p}_p$, as is depicted in Fig. 5.5 for the products of the lowest degree of complexity $\mathbf{p}_1 = [1, 0, 0, 0, 0]$ (base module) to the highest degree of complexity $\mathbf{p}_6 = [1, 1, 1, 0, 0]$:

$$\mathbf{P} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 \end{bmatrix} \tag{5.20}$$

As is depicted in Fig. 5.5, the process is not perfectly balanced and a significant difference between the maxima of the activity times is present. Instead of the described deterministic station times, the proposed more realistic L-R fuzzy sets were used to represent the activity times. According to our expertise, the same strategy was followed with regard to the fuzzification of the activity times as the parameters of the fuzzy set (Eq. 5.4) were set at $b = c$ (therefore, a single maximum was defined) and set to the nominal values (the average cycle times), namely $a = b/15$ and $d = b/10$, respectively. These fuzzy sets were applied to analyse

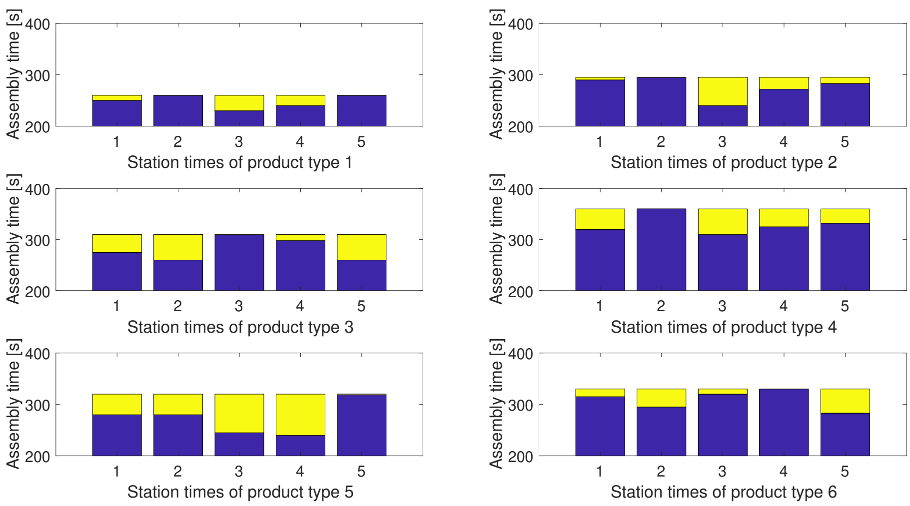

FIGURE 5.5: Station times ($t_{a,w}(k+j|k)$) of different types of products calculated according to the parameter matrices $\mathbf{P}$ and θ of the presented illustrative example. The bars represent different workstations. The blue segments illustrate the station times, while the yellow parts highlight the difference from the maximum time of the bottleneck. As can be seen, the production line is not perfectly balanced and there are significant difference between the station times.

the stochastic simulation by Monte Carlo simulation-based random generation to ensure that the distribution of the generated random variables approximates the membership functions.

The model permits the operators to work ahead of schedule for a certain duration of time. However, since the operators must not disturb each other, none of the elements of the vector $\mathbf{t}_d(k)$ can exceed a critical value c_{ah}, which is usually half of the average cycle time. In that case, the delay time (t_d) is negative, therefore, the operators work ahead of schedule, but according to this defined constraint cannot leave their assigned workstation. When a constant setting time is applied, the cycle time is set to the maximum of the station times calculated using the $\alpha = 0.1$, $c_{crit} = 120$ and $c_{ah} = 120$.

Fig. 5.6 depicts the results when the cycle time was constant. In this case, every operator can complete their designated tasks, but the efficiency of production is low compared to the controlled cycle time set in Fig. 5.7. As can be seen in the subplot at the top of both figures, the same sequences of products were produced in both cases. The subplots in the middle depict show the controlled cycle times, which was constant in the first case, while the subplots at the bottom present how the delays vary in the case of different cycletimes and work stations.

The negative delays show that the operators worked ahead of shedule at given workstation and when the cycle times were constant the system was excessively optimized to prevent stoppages. However, by applying a model predictive control scheme, the system is optimized to prevent stoppages and maintain a high level of productivity.

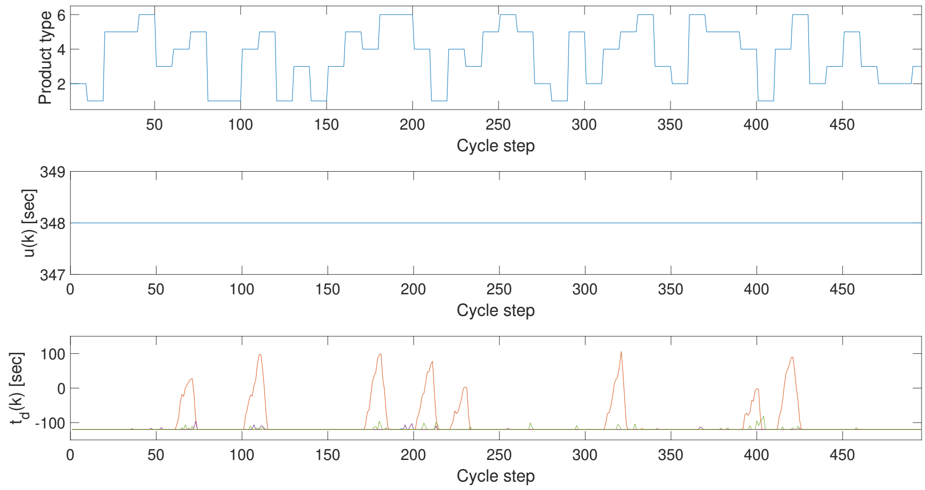

FIGURE 5.6: Production of $N = 500$ products in batches with constant cycle time, $u = 348$. The bottom plot shows the time delay ($t_d(k)$) at every workstation where the colors represent the operators.

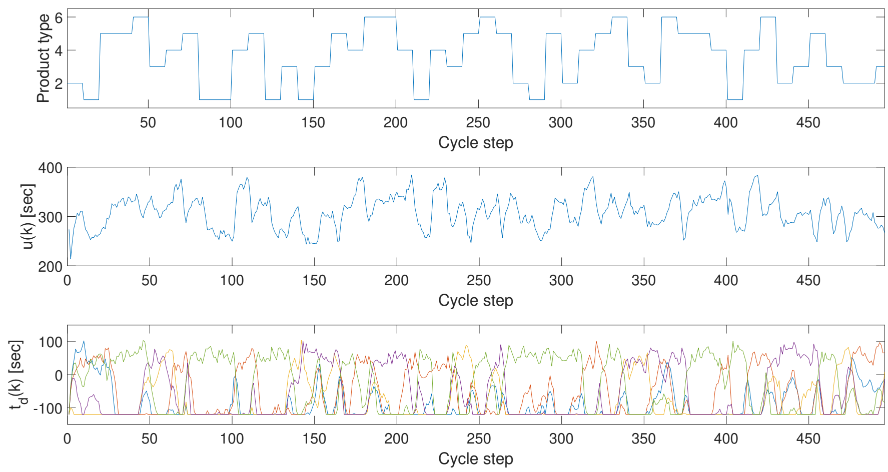

FIGURE 5.7: Production of $N = 500$ products in batches with model predictive control of the cycle time according to the following parameters: $H_p = 2$, $H_c = 1$ and $\alpha = 0.1$. Control of the cycle time maximises the productivity, so the improvement in performance compared to the fixed cycle time is 11%. The bottom plot shows the time delay ($t_d(k)$) at every workstation where the colors represent the operators.

The numerical results are presented in Table 5.1. The performance of the production line is measured as the average production time calculated by dividing the total time required to produce N products by the number of products $t_f(N)/N$, the value of which is sensitive to the number of stoppages since when production has to be stopped, one cycle time is required to restart the conveyor belt.

As is illustrated by the results, when the cycle time is controlled, the productivity of the production line is enhanced by 11%. By decreasing α, the robustness of the controller is increased, thanks to a reduction in the number of stoppages. An increase in the prediction horizon also enhances the degree of robustness. A larger prediction horizon usually results in a slightly slower, balanced response and robust performance.

TABLE 5.1: A comparison between the average production times ($t_f(N)/N$) and number of stoppages when the cycle time is constant and different settings are applied to the controllers.

Scenario	Prod. time [min]	# of stoppages
Constant cycle time, $u = 348$	348.6	0
One-step-ahead predictive control, $\alpha = 0.1$	312.4	6
Model predictive control, $H_p = 5, H_c = 3$, $\alpha = 0.1$	309.4	0
Model predictive control, $H_p = 2, H_c = 1$, $\alpha = 0.1$	309.2	0
One-step-ahead predictive control, $\alpha = 0.05$	309.9	2
Model predictive control, $H_p = 5, H_c = 3$, $\alpha = 0.05$	309.8	0
Model predictive control, $H_p = 2, H_c = 1$, $\alpha = 0.05$	309.5	0

5.5.2 Dynamic cycle time setting at a wire-harness production line

To support the reproducible development of production flow analysis and optimization algorithms, an open-source benchmark problem of a modular wire-harness production line was developed [207, 251]. The core of the system is a paced conveyor. Based on the data published in [171], the number of product types was $N_p = 64$, which was defined as the combination of $N_m = 7$ modules: base module m_1, left- or right-hand drive m_2, normal/hybrid m_3, halogen/LED lights m_4, petrol/diesel engine m_5, 4 doors/5 doors m_6 and manual or automatic gearbox m_7.

The conveyor consisted of $N_w = 10$ workstations (tables). For every table (workstation) one operator was assigned, $N_o = 10$. The activity time of each workstation is illustrated in Fig. 5.8. Further details concerning the applied example can be seen in the appendix and in [207, 251].

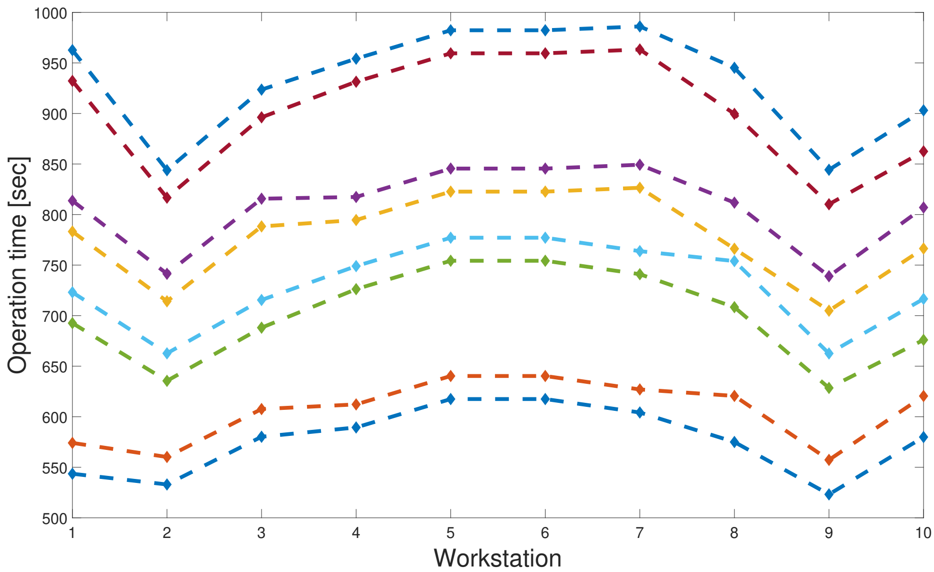

FIGURE 5.8: Station times with regard to the production of different types of modular products calculated based on the parameters given in the Appendix. The lines with different colours represent different product types. A significant difference can be observed in the workload of the operators in terms of the production of simple (basic) and more complex products.

The maximum delay time and working ahead-of-schedule times were both defined as $c_{crit} = 400$ and $c_{ah} = 400$. As is illustrated by the results illustrate in Table 5.2, the control of the cycle time improves the productivity of the production line by 20% which is more significant than the improvement in the previous demonstrative example. The performances of the controllers were evaluated based on the $t_f(N)/N$ average production times and the number of stoppages that are calculated based on the logic incorporated in eq. 5.13. The effects of the parameters are identical to those experienced previously. The decrease in α increases the robustness of the controller, thanks to the decrease in the number of stoppages. The increase in the prediction horizon also leads to an increase in the robustness. A larger prediction horizon usually results in a slightly slower, balanced response and robust performance, however, in this case, the larger control horizon enhances the performance as the length of the production line increases, so the dynamical behaviour of the accumulation of delays is of a higher order. These results are nicely represented in Fig. 5.10 and numerically described in Table 5.2.

TABLE 5.2: Comparison between the average production times ($t_f(N)/N$) and number of stoppages when the cycle time was constant and different settings applied to the controllers when the cycle time of the wire-harness production conveyor was controlled.

Scenario	Prod. time [min]	# of stoppages
Constant cycle time, $u = 1110$	1110.6	0
One-step-ahead predictive control, $\alpha = 0.1$	928.6	6
Model predictive control, $H_p = 5, H_c = 3$, $\alpha = 0.1$	916.4	0
Model predictive control, $H_p = 2, H_c = 1$, $\alpha = 0.1$	917.5	0
One-step-ahead predictive control, $\alpha = 0.05$	920.3	3
Model predictive control, $H_p = 5, H_c = 3$, $\alpha = 0.05$	916.5	0
Model predictive control, $H_p = 2, H_c = 1$, $\alpha = 0.05$	917.5	0

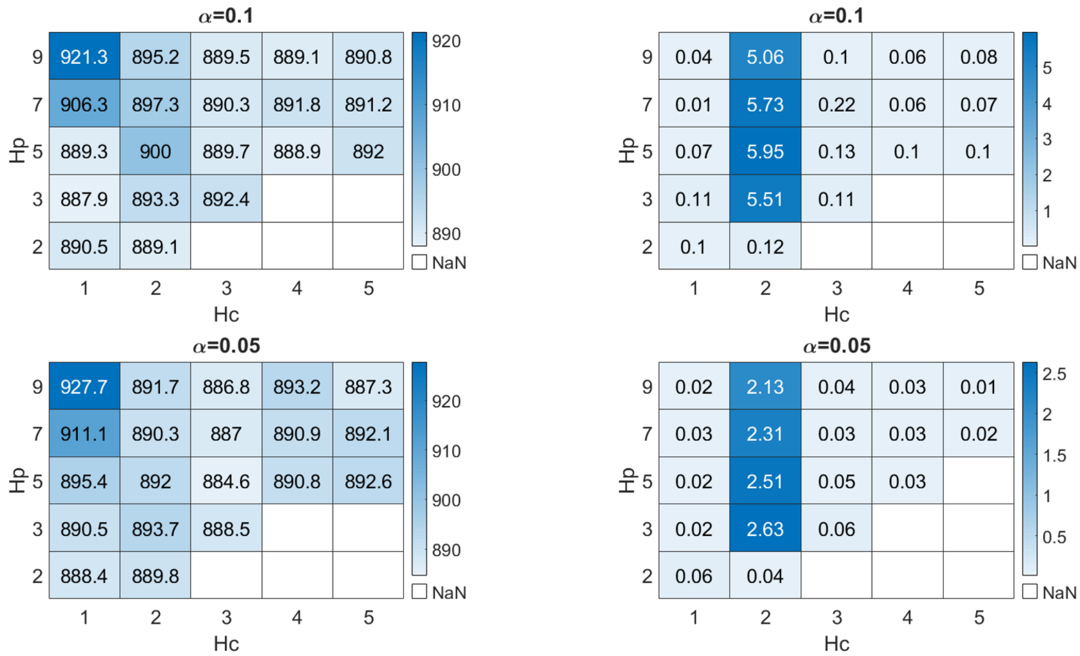

FIGURE 5.9: Systematic analysis of the effects of the H_p, H_c and α parameter values. The heatmaps are based on 100 simulations. The heatmaps on the left show the average production times in minutes, while the ones on the right present the average number of stoppages. The heatmaps at the top and bottom are calculated at $\alpha = 0.1$ and $\alpha = 0.05$, respectively.

The detailed effects of the H_p, H_c, and α parameters are studied based on the systematic analysis of 100 independent simulations of different control tunings. The heatmaps in Figure 5.9 show the average production times in minutes (left) and the average number of stoppages (right). As the results show, the increase of H_p prediction horizon and the α regulation parameters make the performance more robust and sluggish, while the increase of the H_c increases the flexibility of the optimisation that makes the controller more aggressive. As H_c should be smaller than H_p, the combination of these effects results that there is an optimal parameter set at $H_p = 5$, $H_c = 3$, and $\alpha = 0.05$.

In order to prove the scalability of the developed algorithm, a performance analysis was also performed. In this study, the calculation times in the case of three production lines with a different number of workstations were compared. As Figure 5.11 shows, although the number of workstations linearly increases the size of the matrices that has to be inverted, the computational demand at this step is so marginal that the calculation times are not significantly affected in a practical range of the parameters.

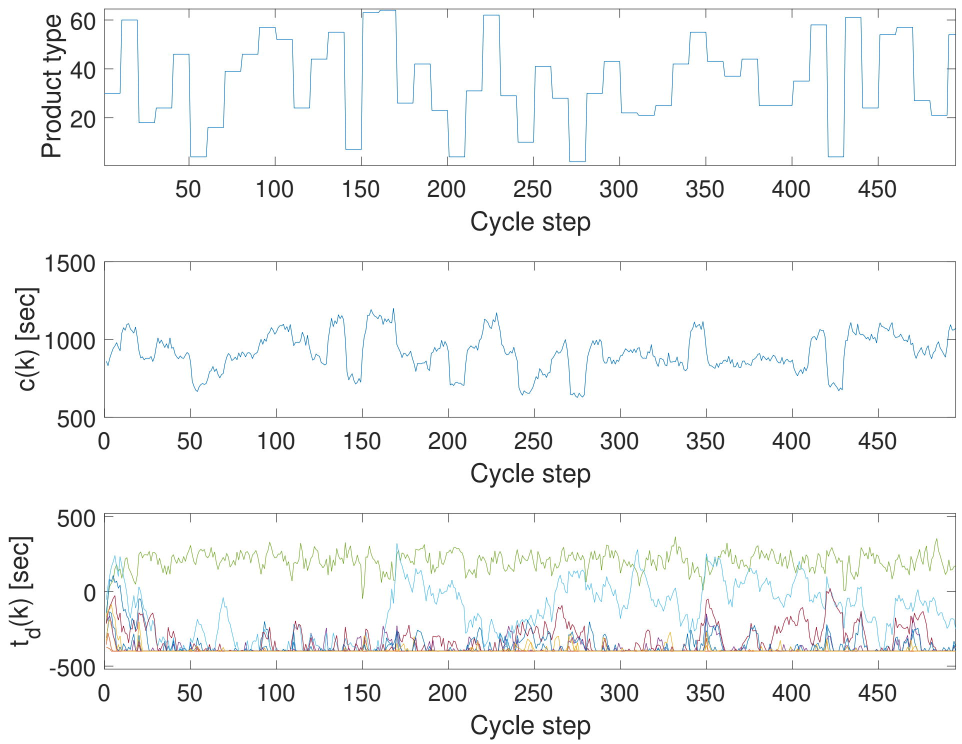

FIGURE 5.10: Production of $N = 500$ products in batches by applying model predictive control with regard to the cycle time of the wire-harness production line, $H_p = 5$, $H_c = 3$, $\alpha = 0.1$. Control of the cycle time maximizes productivity, so performance is enhanced by 20 % in this complex problem compared when the cycle time was constant. The bottom plot shows the time delay $(t_d(k))$ at every workstation where the colors represent the operators.

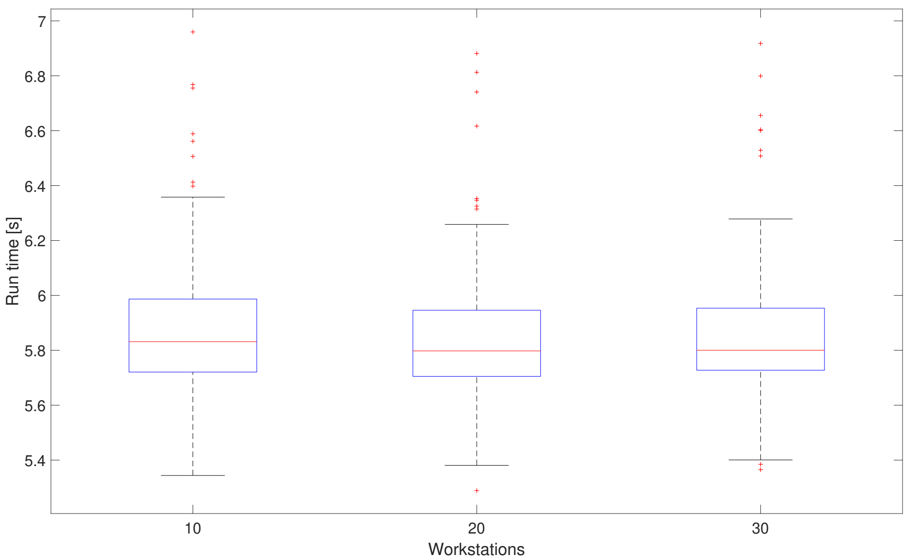

FIGURE 5.11: The scalability of the developed algorithm. The avarage calculation times/cycle in the case of three production lines with different number of workstations. The computational demand of the controller is so marginal that the calculation times are not significantly affected by the complexity of the production line in a practical range of the parameters.

5.6 Conclusion of fuzzy activity time-based model predictive control of open-station assembly lines

The balancing and sequencing of manual mixed-model assembly lines face several challenges due to the complexity of production and the unpredictable nature of human activities. Open-station production is widely used in manufacturing processes as it provides a flexible working environment for the operators because they can work ahead of schedule or try to reduce any backlogs. This flexibility can be applied to increase productivity by sequencing the products. In the present Chapter, another approach was applied which does not dismiss the demand-oriented sequence of the production but tries to maximise the benefits of a well-sequenced production plan and mitigate the difficulties of balancing production lines with multiple products by optimizing the cycle time of the conveyor.

The key idea was to design a model predictive control algorithm to calculate the optimal cycle time and define constraints that minimize the cycle time by preventing delay times from accumulating, any stoppages that result and the subsequent loss of production capacity.

However, in order to effectively calculate and predict the activity times, a reliable model is required as the activity times are uncertain and follow a unique distribution over time. This problem was handled by the application of LR fuzzy sets, thus, the controller could be applied by using a predefined α-cut, which resulted in a new fuzzy model predictive controller scheme.

To be transparent and didactic, the applicability of the proposed method was demonstrated by a simple example. Moreover, the simulator of an industrial wire-harness manufacturing process was proposed to demonstrate the applicability of the control scheme in a more complex environment. The problem is completely industry motivated, however, only the benchmark simulator was published due to confidentiality.

The effectiveness of production was significantly enhanced by applying the defined control scheme, moreover, the effect of the parameters of the controller were investigated and recommendations for their fine-tuning made. Robustness was increased by decreasing the α-cut and increasing the prediction horizon. Therefore, these parameters help to prevent the conveyor from being stopped due to the accumulation of delays.

Thanks to the newest IIoT technologies supported constantly improving measurements, the activity times can be monitored more and more accurately enabling process engineers to construct models of optimal complexity that support the control of production with the required degree of precision and accuracy. Thanks to this development the results can be easily generalised and widely utilised, e.g., the presented model-based controller can be implemented in the real-time optimisation of supply chains, and the proposed fuzzy activity-time models are easily applicable in the scheduling of uncertain business and production processes, which will form the basis of our future research.

Chapter 6

Conclusion

My thesis solved four main problems of flexible manufacturing systems (Figure 6.1), where the blue boxes are represented the developed and proposed solutions for the identified problem in the orange boxes. To understand the problem of the operator at the shop floor, I made an overview of Operator 4.0 concept in Chapter 2. I proved the IIoT based solutions could support the operator in the 4th industrial revolution, and the smart operator handles the challenges of flexible manufacturing with the newest IIoT based technologies. As I proved in the introduction, the main challenge in operator support is the stochastic nature handling. I developed a soft-sensor based real-time performance monitoring algorithms (Chapter 3) to identify the stochastic assembly times in case of modular production thanks to the information integration of BoM and MES. The modular and JIT production is a crucial element of flexible manufacturing, where the importance of changeovers are increased. I developed a targeting model-based survival analysis helps the operator training and process improvement in the case of changeovers. The root cause analysis based anomaly detection shows the losses of the actual changeover (Chapter 4). Finally, based on the monitored indicators, the developed model predictive control is capable of an optimum assembly line control in real-time to handle the mixed-model assembly line optimal cycle time problem. Thanks for the dynamic cycle time control the efficiency optimization is proved in case of mixed production (Chapter 5).

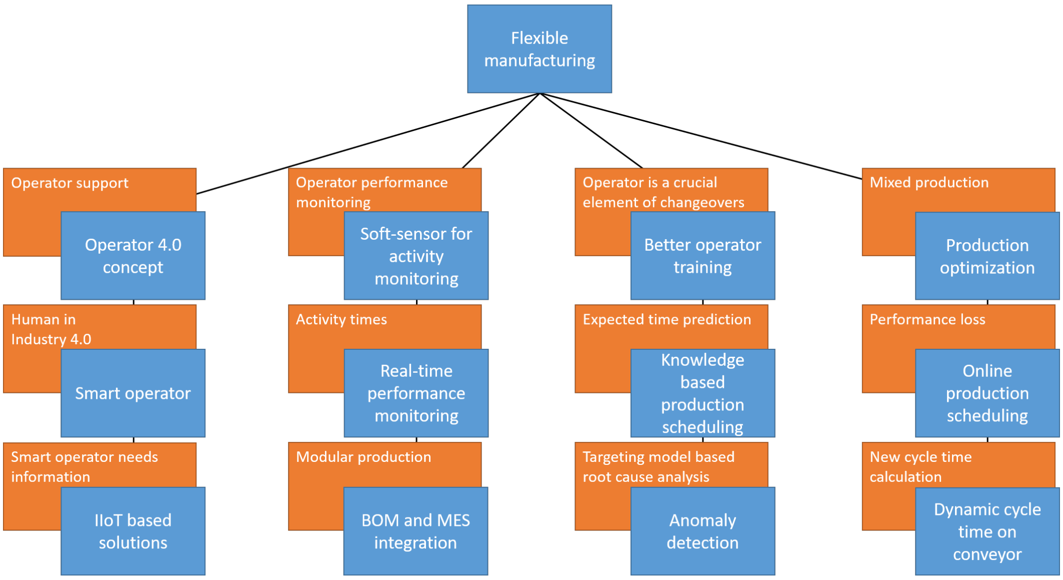

FIGURE 6.1: I developed a data-based solution to solve the problems of flexible manufacturing. I made an overview of Operator 4.0 concept, where the smart operator handles the challenges of flexible. I identified the stochastic assembly times with the developed soft-sensor based real-time performance monitoring algorithms. The proposed targeting model-based survival analysis helps the operator training and process improvement. Based on the fully monitoring system of production, I proposed a model predictive control based conveyor control system.

The applicability of the proposed methodologies is demonstrated on a well-documented benchmark problem of a wire harness manufacturing processes. The activity time monitoring and conveyor control are demonstrated based on a wire-harness manufacturing process with a paced conveyor. However, the proposed algorithm can handle continuous conveyors as well, while the changeover improvements are proved on an anonymized manufacturing example related to the setup of crimping and wire cutting machines. Both three solutions can be used in widely manufacturing problems, thanks to the generalized algorithms.

The new scientific results

1. **I developed a model-based performance monitoring system for activity-time monitoring in production lines**

   Industry 4.0-based human-in-the-loop cyber-physical production systems are transforming the industrial workforce to accommodate the ever-increasing variability of production. Real-time operator support and performance monitoring require accurate information on the activities of operators. The problem with tracing hundreds of activity times is critical due to the enormous variability and complexity of products. A software-sensor-based activity-time and performance measurement system are proposed to handle this problem. Fixture sensors and an IPS were designed and this multi-sensor data merged with product-relevant information to ensure a real-time connection between operator performance and varying product complexity. The presented sensor fusion algorithm combines all sensory and production data such that the estimates of the activity times have less uncertainty than would be possible when these sources were used individually. The estimation of the activity times is based on a linear-in-parameters model. The linear structure of the developed production-monitoring model is adequate as the time consumption of the activities linearly depend on how many primary activities should be performed and what is the number of the built-in components. The number of parameters of activity time estimation models is comparable to the number the number of measurements, the identifiability of the parameters of the model has to be carefully analyzed. For this purpose, I studied the Fisher information/covariance matrix of the estimation problem. A proposed model-based performance monitoring system track to the recursively estimated parameters of the activity-time estimation model. The fully reproducible and realistic simulation study confirms that the indoor positioning system-based integration of primary sensor signals and product-relevant information can be efficiently utilized in terms of the constrained recursive estimation of the operator activity. [207, 251, 227]

2. **I developed a changeover time monitoring system based on survival analysis**

   The losses associated with changeovers are getting more significant in manufacturing due to the high variance of products and requirements for just in time production. I introduced a method for the reduction of these losses based on data-driven root cause analysis and performance management. The developed model takes into account the stochastic nature of complex processes and the work of operators. Based on the inverse of the cumulative distribution function of the activity times, a dynamic targeting model can be developed. The model can be tuned to express the expectations of the process engineers, and the calculated performances can be aggregated to evaluate operator and machine efficiencies. The method is based on models that estimate the product- and operator- dependent changeover times by survival analysis. The root causes of the losses are identified by significance tests the utilized Cox regression models. The resulted models can be used to design a performance management system that takes into account the stochastic nature of the work of the operators. [208]

   The presented application example highlights how the model assumptions can be validated and what kind of information can be extracted based on the analysis of the model.

3. **I developed a model-predictive control for assembly conveyor based on fuzzy-activity times**

   The sequencing and line balancing of manual mixed-model assembly lines are challenging tasks due to the complexity and uncertainty of operator activities. The control of cycle time and the sequencing of production can mitigate the losses due to non-optimal line balancing in the case of open-station production where the operators can work ahead of schedule and try to reduce their backlog. The key idea was to design a model predictive control algorithm to calculate the optimal cycle time and define constraints that minimize the cycle time by preventing delay times from accumulating, any stoppages that result and the subsequent loss of production capacity. I prove a cycle time control algorithm that can improve the efficiency of assembly lines in such situations based on a specially mixed sequencing strategy. A fuzzy-model-based solution has been developed to handle the uncertainty of activity times. As the production process is modular, the fuzzy sets represent the uncertainty of the elementary activity times related to the processing of the modules. The optimistic and pessimistic estimates of the completion of activity times extracted from the fuzzy model are incorporated into a model predictive control algorithm to ensure the constrained optimization of the cycle time. The results confirm that the application of the proposed algorithm is widely applicable in cases where a production line of a supply chain is not well balanced and the activity times are uncertain [208, 209, 207].

Chapter 7

Appendix - Details of the wire-harness production technology

To support the reproducible development of production flow analysis and optimization algorithms, an open source benchmark problem of a modular wire-harness production system was developed. The core of the system is a paced conveyor. Based on data published in [171] and [172], N_p was based on 64 products and defined N_m as a combination of 7 modules: m_1 base module, m_2 as left- or right-hand drive, m_3 normal/hybrid, m_4 halogen/LED lights, m_5 petrol/diesel engine, m_6 4 doors/5 doors and m_7 manual or automatic gearbox. N_a was defined 654 activities/tasks categorized into N_t which consisted of 16 activity types with well-modeled activity times (see Table 7.1). In these activities N_c was equal to 64 different built-in part families (component types) (among these $C_t = 180$ terminals, $C_b = 63$ bandages, $C_c = 25$ clips, and $C_w = 90$ wires). The conveyor N_w consisted of 10 workstations (tables). For every table (workstation) one operator is assigned, $N_o = 10$. The required N_s was also defined as 6 skills of the operators, namely: s_1 - laying cable, s_2 - spot-tying, s_3 - terminal attaching, s_4 - connector installing, s_5 - clip installing, and s_6 - visual testing. N_z was also defined as 6 zones for the workstations to study the distribution of the fixtures on the tables. The related $\mathbf{Z}$ matrix is defined based on the layout of the table and shows the relationship between the activities and zones of the workstation, which facilitates a detailed analysis of the workload in the workstations. The related dataset is freely and fully available on the www.abonyilab.com website.

TABLE 7.1: Types of activities and the related activity times [172]. The activity times are calculated based on fixed and proportional values, e.g., when an operator is laying four wires over one foot, according to the t_4 model, the activity time will be $1 \times 6.9s + 4 \times 4.2 = 23.7s$

ID	Activity	Remark	Unit	Time [s]
t_1	Point-to-point wiring on chassis	Direct wiring	Number of wires	4.6
t_2	Laying in U-channel			4.4
t_3	Laying flat cable			7.7
t_4	Laying wire(s) onto harness jig	Laying flat cable	Base time Per wire	6.9 4.2
t_5	Laying cable connector (one end) onto harness jig	To the same breakout	Base time Per wire	7.4 2.3
t_6	Spot-tying onto cable and cutting it with a pair of scissors			16.6
t_7	Lacing activity		Base time Per additional stitch	1.5 3.6
t_8	Taping activity		Base time Per stitch	1.8 5.0
t_9	Inserting into tube or sleeve		Base time Per inch	3.0 2.4
t_{10}	Attachment of wire terminal	Terminal-block fastening (fork lug)		22.8
t_{11}	Screw fastening of terminal			17.1
t_{12}	Screw-and-nut fastening of terminal			24.7
t_{13}	Circular connector	Installation only		11.3
t_{14}	Rectangular connector	Latch or snap-on		24.0
t_{15}	Clip installation			8.0
t_{16}	Visual testing			120.0

Acronyms

General abbreviation

AMS: Agile Manufacturing System

AoA: Angle of Arrival

AR: Augmented Reality

BLE: Bluetooth Low Energy

BoM: Bill of Materials

BPMN: Business Process Model and Notation

BPR: Business Process Reengineering

CNC: Computer Numerical Control

CoBot: Collaborative Robot

CPS: Cyber-Physical System

CPPS: Cyber-Physical Production System

CS: Computer Science

CSA: Cross Section Area

DIND: Distributed Intelligent Network Device

E-SNS: Enterprise Social Networking Service

FDI: Fault Detection and Isolation

FMS: Flexible Manufacturing System

H-CPS: Human-Cyber-Physical System

H-CPPS: Human-Cyber-Physical Production System

HMI: Human Machine Interface

HR: Human Resources

IoT: Internet of Things

IIoT: Industrial Internet of Things

IPA: Intelligent Personal Assistant

IPS: Indoor Positioning System

iSpace: Intelligent Space

KPI: Key Performance Indicator

MBI: Model-Based Instructions

MES: Manufacturing Execution System

MSDF: Multi-sensor data fusion

NN: Neural Network

OEE: Overall Equipment Effectiveness

OP: observed vs. predicted

PHA: Proportional Hazard Assumption

PwC: PricewaterhouseCoopers

RFID: Radio Frequency IDentification

RSS: Received Signal Strength

RUL: Remaining Useful Life

SFC: Shop Floor Control

SFCS: Shop Floor Control System

SMED: Single Minute Exchange of Die

SS: Signal Strength

ToA: Time of Arrival

UWB: Ultra-wideband

VR: Virtual Reality

Software sensor for activity-time monitoring

$p_1, \ldots, p_{N_p}$: products

$m_1, \ldots, m_{N_m}$: modules

$a_1, \ldots, a_{N_a}$: activities

$c_1, \ldots, c_{N_c}$: components

$w_1, \ldots, w_{N_w}$: workstations

$t_1, \ldots, t_{N_t}$: activity types

$\mathbf{A}$: $(N_p \times N_a)$ activities required to produce a product

$\mathbf{W}$: $(N_a \times N_w)$ workstation assigned for an activity

$\mathbf{B}$: $(N_p \times N_c)$ component/part required to produce a product

$\mathbf{P}$: $(N_p \times N_p)$ module/part family required to produce a product

$\mathbf{C}$: $(N_a \times N_c)$ component/part built in or processed in an activity

$\mathbf{M}$: $(N_a \times N_m)$ activity required to produce a module

$\mathbf{T}$: $(N_a \times N_t)$ category of the activity

$\mathbf{S}^w$: $(N_a \times l_w)$ activity involved over a measured time interval

k: index of the production cycle (discrete time)

$\hat{y}_i^w(k)$: estimation of the individual activity times for work station w in the kth production cycle

$\mathbf{x}^w(k)$: 'efficiency' of the operator, the vector of the estimated local activity times

$\mathbf{x}(k)$: workstation-independent version of $\mathbf{x}^w(k)$

$\mathbf{s}(k)$: sequence of the timestamps recorded by the active fixture sensors

$\mathbf{z}^w(k)$: vector of the sum of the activity times that are situated between the two sensors

α: index of the first sensor of a fixture-sensor pair

β: index of the second sensor of a fixture-sensor pair

$\mathbf{q}_a$: the set of activities required to produce a specific product

$\mathbf{e}^w$: serially uncorrelated white-noise vector of observational errors

$\mathbf{R}^w(k)$: covariance matrix of observational errors

$\mathbf{H}(k)$: time-variable regressors representing the number of activities and built in components

$\mathbf{e}(k)$: the set of the serially uncorrelated white-noise vector of observational errors of the workstations

$\hat{\mathbf{x}}(N)$: estimation error

$\mathbf{Q}$: positive-definite weighting matrix defined as $\mathbf{Q} = (\mathbf{R})^{-1}$

$\mathbf{P}^*$: inverse of the parameter covariance matrix

$\mathbf{A}^*(k)$: State-transition matrix in the Kalman filter represented estimation problem

$\mathbf{K}(k)$: Gain of the Kalman filter/recursive estimator

$\mathbf{L}^w$,$\mathbf{c}^w$: Representation of the linear inequality constraints

$\mathbf{A}_e^w$,$\mathbf{b}_e^w$: Representation of the linear equality constraints

μ_j: vector of Lagrange multiplier associated with equality

λ_j: vector of Lagrange multiplier associated with inequality constraints

Reducing machine setup and changeover times

by survival analysis

T: Specific time limit to survival analysis

$S(t)$: the survival analysis function

t: independent variable as time

n_j: number of activities

d_j: number of completed activities at that j time

$h^i(t, \mathbf{x})$: distribution function derived from the Cox regression

$h_0^i(t)$: baseline hazard function

m: number of switching predictors

n: number of examined activities

b: the Cox regression parameters

$\hat{t}^i(\mathbf{x}, p)$: the nominal time, if the p is equal to 50%

$t^i(\mathbf{x})$: the measured time-based on the machine log

$\mathbf{x}$: feature set

$\mathbf{x}_k$: subset of $\mathbf{x}$

$L^i(p)$: the loss model

$G^i(p)$: the gain model

Fuzzy activity time-based model predictive control

$w = 1, \ldots, N_w$: index of the workstations

$p = 1, \ldots, N_p$: types of the products

$k = 1, \ldots, N$: index of the cycle in the cyclic production of the assembly line

$\pi(k) \in \{1, \ldots, N_p\}$: sequence of produced products (in the k^{th} cycle)

$m = 1, \ldots, N_m$: types of modules

$\mathbf{P}$: $(N_m \times Np)$ binary matrix representing the types of modules with regard to the type of product

$k + j|k$: represents the predicted value from the beginning of cycle k to the beginning of cycle $k + j$

t_a: estimated assembly time of an activity

t_c: sum of the cycle times

t_f: finishing time

t_d: time delay compared to the cycle time

u: actual cycle time

$\mathbf{z}_f$: $(1 \times N_m)$ vector-based representation of the product type that is at the start of the production line (equal to $\mathbf{p}_{\pi(k-w)}$ in cycle k)

$\mathbf{x}_f$: $(1 \times N_w)$ vector-based representation that defines the state of the workstation

$\mathbf{A}_f$: $(N_m N_w \times N_m N_w)$ matrix defining the flow of the assembly line

$\mathbf{B}_f$: $(N_m N_w \times N_m)$ matrix defining how the next product enters the assembly line

$\mathbf{C}_f$: $(N_w N_m \times N_w)$ matrix defining the elementary activity times

Θ: $(N_w \times N_m)$ matrix representing the building block elementary activity times

A_i: required time of the i-th activity

$\mu_{A_i}(t)$: fuzzy membership function

I: interval of LR model

a, b, c, d: constant interval variables

$L(x), R(x)$: non-increasing functions

$\alpha, \alpha \in [0, 1]$: value of α-cut

H_p: prediction horizon

H_c: control horizon

$\mathbf{R}$: weighting matrix of the control actions

c_{crit}: critical delay time

c_{ah}: threshold of the amount of how working ahead of schedule

Bibliography

[1] Michael Rüßmann, Markus Lorenz, Philipp Gerbert, Manuela Waldner, Jan Justus, Pascal Engel, and Michael Harnisch. Industry 4.0: The Future of Productivity and Growth in Manufacturing Industries. *Boston Consulting Group*, 9:1–14, 2015.

[2] Shiyong Wang, Jiafu Wan, Di Li, and Chunhua Zhang. Implementing smart factory of industrie 4.0: An outlook. *International Journal of Distributed Sensor Networks*, 12(1):1–12, 2016.

[3] Ing Reiner Anderl. Industrie 4 . 0 - Advanced Engineering of Smart Products and Smart Production. *International Seminar on High Technology*, 1:1–14, 2014.

[4] Li Da Xu, Eric L Xu, and Ling Li. Industry 4.0: state of the art and future trends. *International Journal of Production Research*, 56(8):2941–2962, 2018.

[5] Kuijper Martin, East Asia, et al. Innovative competition with chinese characteristics. the case of'made in china 2025'in relation to the german industry. B.S. thesis, 2018.

[6] Tian Shubin and Pan Zhi. "made in china 2025" and "industrie 4.0"—in motion together. In *The Internet of Things*, pages 87–113. Springer, 2018.

[7] Shiyong Wang, Jiafu Wan, Daqiang Zhang, Di Li, and Chunhua Zhang. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. *Computer Networks*, 101: 158–168, 2016. doi: 10.1016/j.comnet.2015.12.017.

[8] X. Chai, B. Hou, P. Zou, J. Zeng, and J. Zhou. Indics: An industrial internet platform. In *IEEE International Conference on Cloud and Big Data Computing, Guangzhou, China, accepted*, volume 1, pages 1–1. IEEE, 2018.

[9] Ma Huimin, Xiang Wu, Li Yan, Han Huang, Han Wu, Jie Xiong, and Jinlong Zhang. Strategic plan of "made in china 2025" and its implementation. In *Analyzing the Impacts of Industry 4.0 in Modern Business Environments*, volume 23, pages 1–23. IGI Global, 2018.

[10] Simon Ford and Mélanie Despeisse. Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. *Journal of Cleaner Production*, 137:1573–1587, 2016. ISSN 0959-6526. doi: https://doi.org/10.1016/j.jclepro.2016.04.150. URL `http://www.sciencedirect.com/science/article/pii/S0959652616304395`.

[11] Gisela Lanza, Peter Nyhuis, Sarah Majid Ansari, Thorben Kuprat, and Christoph Liebrecht. Befähigungs-und einführungsstrategien für industrie 4.0. *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, 111(1-2):76–79, 2016.

[12] Moritz Schroter Karl Lichtblau, Edgar Schmitz. Impuls - industrie 4.0-readiness. *Impuls-Stiftung des VDMA, Aachen-Köln*, (77):1–77, 2015.

[13] Andreas Schumacher, Selim Erol, and Wilfried Sihn. A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia CIRP*, 52:161–166, 2016.

[14] John Hawksworth, Richard Berriman, and Saloni Goel. Will robots really steal our jobs?: an international analysis of the potential long term impact of automation. `http://pwc.blogs.com/economics_in_business/2018/02/will-robots-really-steal-our-jobs.html`, 2018. [Online; accessed 20-July-2018].

[15] Carl Benedikt Frey and Michael Osborne. The future of employment: How susceptible are jobs to computerisation. `https://www.oxfordmartin.ox.ac.uk/publications/view/1314`, 2013. [Online; accessed 20-July-2018].

[16] PricewaterhouseCooper. Workforce of the future: The competing forces shaping 2030. `https://www.pwc.com/gx/en/services/people-organisation/publications/workforce-of-the-future.html`, 2017. [Online; accessed 20-July-2018].

[17] Yongxin Liao, Fernando Deschamps, Eduardo de Freitas Rocha Loures, and Luiz Felipe Pierin Ramos. Past, present and future of industry 4.0-a systematic literature review and research agenda proposal. *International journal of production research*, 55(12):3609–3629, 2017.

[18] László Monostori. Cyber-physical production systems: Roots, expectations and r&d challenges. *Procedia CIRP*, 17:9–13, 2014.

[19] Keliang Zhou, Taigang Liu, and Lifeng Zhou. Industry 4.0: Towards future industrial opportunities and challenges. In *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, pages 2147–2152. IEEE, 2015. doi: 10.1109/FSKD.2015.7382284.

[20] Raja Parasuraman, Thomas B. Sheridan, and Christopher D. Wickens. A model of types and levels of human interaction with automation. *IEEE Transactions on Systems, Man and Cybernetics*, 30:286–297, 2000.

[21] Sirajum Munir, John A Stankovic, Chieh-Jan Mike Liang, and Shan Lin. Cyber physical system challenges for human-in-the-loop control. In *Presented as part of the 8th International Workshop on Feedback Computing*, volume 4, pages 1–4. USENIX, 2013. URL `https://www.usenix.org/conference/feedbackcomputing13/workshop-program/presentation/Munir`.

[22] Peter A Hancock, Richard J Jagacinski, Raja Parasuraman, Christopher D Wickens, Glenn F Wilson, and David B Kaber. Human-automation interaction research: past, present, and future. *Ergonomics in Design*, 21(2):9–14, 2013.

[23] Eija Kaasinen, Marja Liinasuo, Franziska Schmalfuß, Hanna Koskinen, Susanna Aromaa, Päivi Heikkilä, Anita Honka, Sebastian Mach, and Timo

Malm. A worker-centric design and evaluation framework for operator 4.0 solutions that support work well-being. In *IFIP Working Conference on Human Work Interaction Design*, pages 263–282. Springer, 2018.

[24] Stephan Weyer, Mathias Schmitt, Moritz Ohmer, and Dominic Gorecky. Towards industry 4.0-standardization as the crucial challenge for highly modular, multi-vendor production systems. *Ifac-Papersonline*, 48(3):579–584, 2015.

[25] Frits K. Pil and Matthias Holweg. Linking product variety to order-fulfillment strategies. *Interfaces*, 34(5):394–403, 2004. ISSN 00922102. doi: 10.1287/inte.1040.0092.

[26] Pablo Guzmán Ferradás and Konstantinos Salonitis. Improving changeover time: a tailored smed approach for welding cells. *Procedia CIRP*, 7:598–603, 2013.

[27] Filipe Ferreira, José Faria, Américo Azevedo, and Ana Luísa Marques. Industry 4.0 as enabler for effective manufacturing virtual enterprises. In *Working Conference on Virtual Enterprises*, pages 274–285. Springer, 2016.

[28] Markus Lorenz, Michael Ruessmann, Rainer Strack, Knud Lasse Lueth, and Moritz Bolle. Man and machine in industry 4.0: How will technology transform the industrial workforce through 2025, 2015. [Online; accessed 06-July-2018].

[29] David Romero, Peter Bernus, Ovidiu Noran, Johan Stahre, and Åsa Fast-Berglund. The operator 4.0: Human cyber-physical systems & adaptive automation towards human-automation symbiosis work systems. In *Advances in Production Management Systems. Initiatives for a Sustainable World*, volume 10, pages 677–686. Springer, 2016.

[30] David Romero, Johan Stahre, Thorsten Wuest, Ovidiu Noran, Peter Bernus, Åsa Fast-Berglund, and Dominic Gorecky. Towards an operator 4.0 typology: A human-centric perspective on the fourth industrial revolution technologies.

In *International conference on computers and industrial engineering (CIE46) proceedings*, volume 11, pages 1–11, 10 2016.

[31] Valeria Villani, Fabio Pini, Francesco Leali, and Cristian Secchi. Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications. *Mechatronics*, 19:1–19, 2018.

[32] Philip Russom. Big data analytics. *TDWI Best Practices Report, Fourth Quarter*, 19(4):1–34, 2011.

[33] Hsinchun Chen, Roger HL Chiang, and Veda C Storey. Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, 24:1165–1188, 2012.

[34] Te-Lien Chou and Lih-Juan ChanLin. Augmented reality smartphone environment orientation application: A case study of the fu-jen university mobile campus touring system. *Procedia-Social and Behavioral Sciences*, 46:410–416, 2012.

[35] Katariina Penttila, Nina Pere, M Sioni, Lauri Sydanheimo, and Markku Kivikoski. Use and interface definition of mobile rfid reader integrated in a smart phone. In *Proceedings of the Ninth International Symposium on Consumer Electronics, 2005. (ISCE 2005)*, pages 353–358. IEEE, 2005. doi: 10.1109/ISCE.2005.1502402.

[36] Jim Davis, Thomas Edgar, James Porter, John Bernaden, and Michael Sarli. Smart manufacturing, manufacturing intelligence and demand-dynamic performance. *Computers & Chemical Engineering*, 47:145–156, 2012.

[37] Jianlong Zhou, Ivan Lee, Bruce Thomas, Roland Menassa, Anthony Farrant, and Andrew Sansome. In-situ support for automotive manufacturing using spatial augmented reality. *International Journal of Virtual Reality*, 11:33–41, 2012.

[38] Alex Olwal, Jonny Gustafsson, and Christoffer Lindfors. Spatial augmented reality on industrial cnc-machines. In *The Engineering Reality of Virtual Reality 2008*, volume 9, pages 1–9. International Society for Optics and Photonics, 2008.

[39] Andrew YC Nee, SK Ong, George Chryssolouris, and Dimitris Mourtzis. Augmented reality applications in design and manufacturing. *CIRP Annals - Manufacturing Technology*, 61(2):657–679, 2012.

[40] Baxter & Sawyer. Rethink robotics. `http://www.rethinkrobotics.com/sawyer-intera-3/`, 2015.

[41] Karen Myers, Pauline Berry, Jim Blythe, Ken Conley, Melinda Gervasio, Deborah L McGuinness, David Morley, Avi Pfeffer, Martha Pollack, and Milind Tambe. An intelligent personal assistant for task and time management. *AI Magazine*, 28(2):1–27, 2007.

[42] Thorsten Wuest, Karl Hribernik, and Klaus-Dieter Thoben. Can a product have a facebook? a new perspective on product avatars in product lifecycle management. In *Product Lifecycle Management. Towards Knowledge-Rich Enterprises*, pages 400–410. Springer, 2012.

[43] Nahema Sylla, Vincent Bonnet, Frédéric Colledani, and Philippe Fraisse. Ergonomic contribution of able exoskeleton in automotive industry. *International Journal of Industrial Ergonomics*, 7(44):475–481, 2014.

[44] Tariq S Mujber, Tamas Szecsi, and Mohammed SJ Hashmi. Virtual reality applications in manufacturing process simulation. *Journal of Materials Processing Technology*, 155-156:1834–1838, 2004. URL `http://www.sciencedirect.com/science/article/pii/S0924013604005618`. Proceedings of the International Conference on Advances in Materials and Processing Technologies: Part 2.

[45] Benjamin J Darter and Jason M Wilken. Gait training with virtual reality-based real-time feedback: Improving gait performance following transfemoral amputation. *Physical Therapy*, 91(9):1385–1394, 2011.

[46] László Horváth and Imre J Rudas. Role of information content in multipurpose virtual engineering space. In *2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI)*, pages 99–104. IEEE, 2017. doi: 10.1109/SAMI.2017.7880283.

[47] Robson Marinhoda Silva, Israel F. Benítez-Pina, Mauricio F. Blos, Diolino J. Santos Filho, and Paulo E. Miyagi. Modeling of reconfigurable distributed manufacturing control systems. *IFAC-PapersOnLine*, 48(3):1284–1289, 2015. URL `https://doi.org/10.1016/j.ifacol.2015.06.262`.

[48] Syed Imran Shafiq, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. Virtual engineering factory: Creating experience base for industry 4.0. *Cybernetics and Systems*, 47(1-2):32–47, 2016. URL `https://doi.org/10.1080/01969722.2016.1128762`.

[49] Morteza Ghobakhloo. The future of manufacturing industry: a strategic roadmap toward industry 4.0. *Journal of Manufacturing Technology Management*, 29(6):910–936, 2018. doi: 10.1108/JMTM-02-2018-0057.

[50] Jorge Posada, Carlos Toro, Inigo Barandiaran, David Oyarzun, Didier Stricker, Raffaele de Amicis, Eduardo B. Pinto, Peter Eisert, Jürgen Döllner, and Ivan Vallarino. Visual computing as a key enabling technology for industrie 4.0 and industrial internet. *IEEE Computer Graphics and Applications*, 35(2):26–40, Mar 2015. ISSN 0272-1716. doi: 10.1109/MCG.2015.45.

[51] Alasdair Gilchrist. *Industry 4.0: the industrial internet of things*. Springer, 2016.

[52] Morteza Ghobakhloo and Adel Azar. Business excellence via advanced manufacturing technology and lean-agile manufacturing. *Journal of Manufacturing Technology Management*, 29(1):2–24, 2018. doi: {10.1108/JMTM-03-2017-0049}.

[53] David Pérez Perales, F Alarcón, and Andrés Boza. *Industry 4.0: A Classification Scheme*, pages 343–350. 01 2018. ISBN 978-3-319-58408-9.

[54] Pingyu Jiang, Kai Ding, and Jiewu Leng. Towards a cyber-physical-social-connected and service-oriented manufacturing paradigm: Social manufacturing. *Manufacturing Letters*, 7:15–21, 2016. ISSN 2213-8463. doi: https://doi.org/10.1016/j.mfglet.2015.12.002. URL `http://www.sciencedirect.com/science/article/pii/S221384631500022X`.

[55] MPDV. Industry 4.0: Mes supports decentralization. `https://www.mpdv.com/media/company/company_magazine/NEWS_International_2015.pdf`, 2015. [Online; accessed 20-July-2018].

[56] Aitor Moreno, Gorka Velez, Aitor Ardanza, Iñigo Barandiaran, Álvaro Ruíz de Infante, and Raúl Chopitea. Virtualisation process of a sheet metal punching machine within the industry 4.0 vision. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 11(2):365–373, May 2017. ISSN 1955-2505. doi: 10.1007/s12008-016-0319-2. URL `https://doi.org/10.1007/s12008-016-0319-2`.

[57] W. Dai, V. N. Dubinin, J. H. Christensen, V. Vyatkin, and X. Guan. Toward self-manageable and adaptive industrial cyber-physical systems with knowledge-driven autonomic service management. *IEEE Transactions on Industrial Informatics*, 13(2):725–736, April 2017. ISSN 1551-3203.

[58] Göran Adamson, Lihui Wang, and Philip Moore. Feature-based control and information framework for adaptive and distributed manufacturing in cyber physical systems. *Journal of Manufacturing Systems*, 43: 305–315, 2017. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2016.12.003. URL `http://www.sciencedirect.com/science/article/pii/S0278612516300905`. High Performance Computing and Data Analytics for Cyber Manufacturing.

[59] X. Jin, W. M. Haddad, and T. Yucelen. An adaptive control architecture for mitigating sensor and actuator attacks in cyber-physical systems. *IEEE Transactions on Automatic Control*, 62(11):6058–6064, Nov 2017. ISSN 0018-9286.

[60] Xu Jin, Wassim M Haddad, and Tomohisa Hayakawa. An adaptive control architecture for cyber-physical system security in the face of sensor and actuator attacks and exogenous stochastic disturbances. *Cyber-Physical Systems*, 4(1):39–56, 2018.

[61] Jay Lee, Behrad Bagheri, and Hung-An Kao. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3:18–23, 2015.

[62] Shreyas Suresh Rao and Ashalatha Nayak. Enterprise ontology model for tacit knowledge externalization in socio-technical enterprises. *Interdisciplinary Journal of Information, Knowledge and Management*, 12:99–124, 2017.

[63] Michael Polanyi. *The tacit dimension*. Garden City, 1992.

[64] Elizabeth A. Smith. The role of tacit and explicit knowledge in the workplace. *Journal of Knowledge Management*, 5(4):311–321, 2001. doi: 10.1108/13673270110411733. URL `https://doi.org/10.1108/13673270110411733`.

[65] T.L. Johnson, S.R. Fletcher, W. Baker, and R.L. Charles. How and why we need to capture tacit knowledge in manufacturing: Case studies of visual inspection. *Applied Ergonomics*, 74:1–9, 2019. ISSN 0003-6870. doi: https://doi.org/10.1016/j.apergo.2018.07.016. URL `http://www.sciencedirect.com/science/article/pii/S0003687018302278`.

[66] Denham L. Phipps, George H. Meakin, and Paul C.W. Beatty. Extending hierarchical task analysis to identify cognitive demands andinformation design requirements. *Applied Ergonomics*, 42(5):741–748, 2011. ISSN 0003-6870. doi: https://doi.org/10.1016/j.apergo.2010.11.009. URL `http://www.sciencedirect.com/science/article/pii/S0003687010001961`.

[67] J. Everitt, S. Fletcher, and A. Caird-Daley. Task analysis of discrete and continuous skills: a dual methodology approach to human skills capture for automation. *Theoretical Issues in Ergonomics Science*, 16(5):513–532,

2015. doi: 10.1080/1463922X.2015.1028508. URL https://doi.org/10.1080/1463922X.2015.1028508.

[68] W. X. Ng, H. K. Chan, W. K. Teo, and I. Chen. Programming a robot for conformance grinding of complex shapes by capturing the tacit knowledge of a skilled operator. *IEEE Transactions on Automation Science and Engineering*, 14(2):1020–1030, April 2017. ISSN 1545-5955. doi: 10.1109/TASE.2015.2474708.

[69] Mite Tomov, Mikolaj Kuzinovski, and Piotr Cichosz. Development of mathematical models for surface roughness parameter prediction in turning depending on the process condition. *International Journal of Mechanical Sciences*, 113:120–132, 2016. ISSN 0020-7403. doi: https://doi.org/10.1016/j.ijmecsci.2016.04.015. URL http://www.sciencedirect.com/science/article/pii/S0020740316300364.

[70] W.B. Lee and C.F. Cheung. A dynamic surface topography model for the prediction of nano-surface generation in ultra-precision machining. *International Journal of Mechanical Sciences*, 43(4):961–991, 2001. ISSN 0020-7403. doi: https://doi.org/10.1016/S0020-7403(00)00050-3. URL http://www.sciencedirect.com/science/article/pii/S0020740300000503.

[71] Xiaohong Lu, Haixing Zhang, Zhenyuan Jia, Yixuan Feng, and Steven Y. Liang. Floor surface roughness model considering tool vibration in the process of micro-milling. *The International Journal of Advanced Manufacturing Technology*, 94(9):4415–4425, Feb 2018. ISSN 1433-3015. doi: 10.1007/s00170-017-1123-2. URL https://doi.org/10.1007/s00170-017-1123-2.

[72] G. Urbikain and L.N. López de Lacalle. Modelling of surface roughness in inclined milling operations with circle-segment end mills. *Simulation Modelling Practice and Theory*, 84:161–176, 2018. ISSN 1569-190X. doi: https://doi.org/10.1016/j.simpat.2018.02.003. URL http://www.sciencedirect.com/science/article/pii/S1569190X18300182.

[73] Kim J Vicente*, Randall J Mumaw, and Emilie M Roth. Operator monitoring in a complex dynamic work environment: A qualitative cognitive model based on field observations. *Theoretical Issues in Ergonomics Science*, 5(5): 359–384, 2004.

[74] Fatma Nasoz, Kaye Alvarez, Christine L Lisetti, and Neal Finkelstein. Emotion recognition from physiological signals using wireless sensors for presence technologies. *Cognition, Technology & Work*, 6(1):4–14, 2004.

[75] Prahalad K Rao, Jia Peter Liu, David Roberson, Zhenyu James Kong, and Christopher Williams. Online real-time quality monitoring in additive manufacturing processes using heterogeneous sensors. *Journal of Manufacturing Science and Engineering*, 6(6):1–6, 2015.

[76] H Almagrabi, A Malibari, and J McNaught. A survey of quality prediction of product reviews. *International Journal of Advanced Computer Science and Applications*, 10(11):49–58, 2015.

[77] AK Bejczy. Virtual reality in manufacturing. In *Re-engineering for Sustainable Industrial Production*, volume 13, pages 48–60. Springer, 1997.

[78] Mohd Fairuz Shiratuddin and Abdul Nasir Zulkifli. Virtual reality in manufacturing. In *Management Education for the 21st Century*, 2001. URL `http://researchrepository.murdoch.edu.au/id/eprint/9840/`.

[79] Sándor Kopácsi and Ferenc Sárközy. Virtual reality in manufacturing. `http://old.sztaki.hu/~kopacsi/vr/vr_main.htm`, 2001. [Online; accessed 20-July-2018].

[80] Ronald T Azuma. A survey of augmented reality. *Presence: Teleoperators & Virtual Environments*, 6(4):355–385, 1997.

[81] Thomas P Caudell and David W Mizell. Augmented reality: an application of heads-up display technology to manual manufacturing processes. In *Proceedings of the Twenty-Fifth Hawaii International Conference on System Sciences*, volume 2, pages 659–669. IEEE, 1992.

[82] Andrew YC Nee and Soh-Khim Ong. Virtual and augmented reality applications in manufacturing. *IFAC proceedings volumes*, 46(9):15–26, 2013.

[83] Eric J Tuegel, Anthony R Ingraffea, Thomas G Eason, and S Michael Spottswood. Reengineering aircraft structural life prediction using a digital twin. *International Journal of Aerospace Engineering*, 15:1–15, 2011.

[84] Fei Tao, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, and Fangyuan Sui. Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, 4(9-12):3563–3576, 2018.

[85] Stefan Boschert and Roland Rosen. *Digital Twin—The Simulation Aspect*, volume 16, pages 59–74. Springer, 2016.

[86] Zhao Xiaobo and Katsuhisa Ohno. Algorithms for sequencing mixed models on an assembly line in a JIT production system. *Computers Industrial Engineering*, 32(1):47–56, 1997.

[87] Zhao Xiaobo, Katsuhisa Ohno, and Hon-Shiang Lau. A Balancing Problem for Mixed Model Assembly Lines with a Paced Moving Conveyor. *Naval Research Logistics*, 19:446–464, 2004. doi: 10.1002/nav.10116.

[88] Zhao Xiaobo and Katsuhisa Ohno. Properties of a sequencing problem for a mixed model assembly line with conveyor stoppages. *European Journal of Operational Research*, 11:560–570, 2000. ISSN 03772217. doi: 10.1016/S0377-2217(99)00198-8.

[89] Zhao Xiaobo, Zhaoying Zhou, and Ainishet Asres. Note on Toyota's goal of sequencing mixed models on an assembly line. *Computers and Industrial Engineering*, 36(1):57–65, 1999. ISSN 03608352. doi: 10.1016/S0360-8352(98)00113-2.

[90] John C Barrett. A monte carlo simulation of human reproduction. *Genus*, 22:1–22, 1969.

[91] Samik Raychaudhuri. Introduction to monte carlo simulation. In *2008 Winter Simulation Conference*, pages 91–100. IEEE, 2008.

[92] Giovanni C Migliaccio, Tao Cheng, Umberto C Gatti, and Jochen Teizer. Data fusion of real-time location sensing (rtls) and physiological status monitoring (psm) for ergonomics analysis of construction workers. In *The 19th Triennial CIB World Building Congress, Brisbane, Queensland, Australia*, volume 12, pages 1–12, 2013.

[93] Emil M Petriu, Nicolas D Georganas, Dorina C Petriu, Dimitrios Makrakis, and Voicu Z Groza. Sensor-based information appliances. *IEEE Instrumentation and Measurement Magazine*, 3(4):31–35, 2000.

[94] Xiang T. R. Kong, Hao Luo, George Q. Huang, and Xuan Yang. Industrial wearable system: the human-centric empowering technology in industry 4.0. *Journal of Intelligent Manufacturing*, 17:1–17, Apr 2018. ISSN 1572-8145. doi: 10.1007/s10845-018-1416-9. URL `https://doi.org/10.1007/s10845-018-1416-9`.

[95] Xiang TR Kong, Xuan Yang, George Q Huang, and Hao Luo. The impact of industrial wearable system on industry 4.0. In *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, pages 1–6. IEEE, 2018.

[96] Hui Liu, Houshang Darabi, Pat Banerjee, and Jing Liu. Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 14(6):1067–1080, 2007.

[97] Yanying Gu, Anthony Lo, and Ignas Niemegeers. A survey of indoor positioning systems for wireless personal networks. *IEEE Communications Surveys & Tutorials*, 20(1):13–32, 2009.

[98] Rainer Mautz and Sebastian Tilch. Survey of optical indoor positioning systems. In *2011 International Conference on Indoor Positioning and Indoor Navigation*, pages 1–7. IEEE, 2011.

[99] Samer S Saab and Zahi S Nakad. A standalone rfid indoor positioning system using passive tags. *IEEE Transactions on Industrial Electronics*, 10 (5):1961–1970, 2011.

[100] Rainer Mautz. Indoor positioning technologies. *ETH Zurich, Department of Civil, Environmental and Geomatic Engineering*, 129:1–129, 2012.

[101] Henning Kagermann, Johannes Helbig, Ariane Hellinger, and Wolfgang Wahlster. *Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group*. Forschungsunion, 2013.

[102] J-H Lee and Hideki Hashimoto. Intelligent space, its past and future. In *Industrial Electronics Society, 1999. IECON'99 Proceedings. The 25th Annual Conference of the IEEE*, volume 6, pages 126–131. IEEE, 1999.

[103] Hideki Hashimoto. Intelligent space: Interaction and intelligence. *Artificial Life and Robotics*, 7(3):79–85, 2003.

[104] Houyi Yan, Kui Zhu, and Yunxiang Ling. The user-resource-task model in intelligent interaction space. In *2015 4th International Conference on Computer Science and Network Technology (ICCSNT)*, volume 01, pages 768–771. IEEE, 2015.

[105] Jiehan Zhou, Teemu Leppanen, Erkki Harjula, Mika Ylianttila, Timo Ojala, Chen Yu, Hai Jin, and Laurence Tianruo Yang. Cloudthings: A common architecture for integrating the internet of things with cloud computing. In *Computer Supported Cooperative Work in Design (CSCWD), 2013 IEEE 17th International Conference on*, pages 651–657. IEEE, 2013.

[106] Cs Szász. Reconfigurable electronics application in intelligent space developments. *International Review of Applied Sciences and Engineering*, 8(2): 107–111, 2017.

[107] Joo-Ho Lee and Hideki Hashimoto. Intelligent space — concept and contents. *Advanced Robotics*, 16(3):265–280, 2002.

[108] Nils Krahnstoever, Jens Rittscher, P Tu, Kevin Chean, and T Tomlinson. Activity recognition using visual tracking and rfid. In *2005 Seventh IEEE Workshops on Applications of Computer Vision (WACV/MOTION'05) - Volume 1*, volume 1, pages 494–500. IEEE, 2005.

[109] Javad Majrouhi Sardroud. Influence of rfid technology on automated management of construction materials and components. *Scientia Iranica*, 19 (3):381–392, 2012. ISSN 1026-3098. doi: https://doi.org/10.1016/j.scient.2012.02.023. URL `http://www.sciencedirect.com/science/article/pii/S1026309812000727`.

[110] George Q Huang, YF Zhang, and PY Jiang. Rfid-based wireless manufacturing for walking-worker assembly islands with fixed-position layouts. *Robotics and Computer-Integrated Manufacturing*, 9(4):469–477, 2007.

[111] George Q Huang, YF Zhang, and PY Jiang. Rfid-based wireless manufacturing for real-time management of job shop wip inventories. *The International Journal of Advanced Manufacturing Technology*, 13(7):752–764, 2008.

[112] Ichiro Satoh. A mobile agent-based framework for location-based services. In *2004 IEEE International Conference on Communications (IEEE Cat. No.04CH37577)*, volume 3, pages 1355–1359. IEEE, 2004.

[113] H Chao. The non-specific intelligent guided-view system based on rfid technology. In *19th International Conference on Advanced Information Networking and Applications (AINA'05) Volume 1 (AINA papers)*, volume 2, pages 580–585. IEEE, 2005.

[114] Joshua R Smith, Kenneth P Fishkin, Bing Jiang, Alexander Mamishev, Matthai Philipose, Adam D Rea, Sumit Roy, and Kishore Sundara-Rajan. Rfid-based techniques for human-activity detection. *Communications of the ACM*, 6(9):39–44, 2005.

[115] Daniel Leitold, Agnes Vathy-Fogarassy, Kristof Varga, and Janos Abonyi. Rfid-based task time analysis for shop floor optimization. In *2018 IEEE*

International Conference on Future IoT Technologies (Future IoT), pages 1–6. IEEE, 2018.

[116] Thomas Stiefmeier, Daniel Roggen, Georg Ogris, Paul Lukowicz, and Gerhard Tröster. Wearable activity tracking in car manufacturing. *IEEE Pervasive Computing*, 7(2):1–7, 2008.

[117] Heli Koskimaki, Ville Huikari, Pekka Siirtola, Perttu Laurinen, and Juha Roning. Activity recognition using a wrist-worn inertial measurement unit: A case study for industrial assembly lines. In *2009 17th Mediterranean Conference on Control and Automation*, pages 401–405. IEEE, 2009.

[118] Jamie A Ward, Paul Lukowicz, Gerhard Troster, and Thad E Starner. Activity recognition of assembly tasks using body-worn microphones and accelerometers. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(10):1553–1567, 2006.

[119] Ville Huikari, Heli Koskimäki, Pekka Siirtola, and Juha Röning. User-independent activity recognition for industrial assembly lines-feature vs. instance selection. In *5th International Conference on Pervasive Computing and Applications*, pages 307–312. IEEE, 2010.

[120] Athanasios S Voulodimos, Nikolaos D Doulamis, Dimitrios I Kosmopoulos, and Theodora A Varvarigou. Improving multi-camera activity recognition by employing neural network based readjustment. *Applied Artificial Intelligence*, 26(1-2):97–118, 2012.

[121] Soo-Cheol Kim, Young-Sik Jeong, and Sang-Oh Park. Rfid-based indoor location tracking to ensure the safety of the elderly in smart home environments. *Personal and Ubiquitous Computing*, 17(8):1699–1707, 2013.

[122] Bartlomiej Gladysz, Krzysztof Santarek, and Cezary Lysiak. Dynamic spaghetti diagrams. a case study of pilot rtls implementation. In *Intelligent Systems in Production Engineering and Maintenance – ISPEM 2017*, pages 238–248. Springer, 2018.

[123] Zhixin Yang, Pengbo Zhang, and Lei Chen. Rfid-enabled indoor positioning method for a real-time manufacturing execution system using os-elm. *Neurocomputing*, 14:121–133, 2016.

[124] Matthias Blum and Guenther Schuh. Towards a data-oriented optimization of manufacturing processes. In *Proceedings of the 19th International Conference on Enterprise Information Systems*, volume 8, pages 257–264, 2017.

[125] Diana Hodgins and Derek Sirnmonds. The electronic nose and its application to the manufacture of food products. *Journal of Analytical Methods in Chemistry*, 7(5):179–185, 1995.

[126] Guido Appenzeller, Joo-Ho Lee, and Hideki Hashimoto. Building topological maps by looking at people: An example of cooperation between intelligent spaces and robots. In *Proceedings of the 1997 IEEE/RSJ International Conference on Intelligent Robot and Systems. Innovative Robotics for Real-World Applications. IROS '97*, volume 3, pages 1326–1333. IEEE, 1997.

[127] Gerald J Agin. Computer vision systems for industrial inspection and assembly. *Computer*, 13(5):11–20, 1980.

[128] Robert M Haralick and Linda G Shapiro. *Computer and robot vision*. Addison-Wesley Reading, 1st edition, 1992.

[129] Shenchang Eric Chen. Quicktime vr: An image-based approach to virtual environment navigation. In *Proceedings of the 22nd Annual Conference on Computer Graphics and Interactive Techniques*, pages 29–38. ACM, 1995.

[130] Christoph Maggioni. A novel gestural input device for virtual reality. In *Proceedings of IEEE Virtual Reality Annual International Symposium*, pages 118–124. IEEE, 1993.

[131] Sven Fleck and Wolfgang Strasser. Adaptive probabilistic tracking embedded in a smart camera. In *2005 IEEE Computer Society Conference on Computer*

Vision and Pattern Recognition (CVPR'05) - Workshops, pages 134–134. IEEE, 2005.

[132] Chuanying Zhai, Zhuo Zou, Qin Zhou, Jia Mao, Qiang Chen, Hannu Tenhunen, Lirong Zheng, and Lida Xu. A 2.4-ghz ism rf and uwb hybrid rfid real-time locating system for industrial enterprise internet of things. *Enterprise Information Systems*, 11(6):909–926, 2017.

[133] Dirk Hahnel, Wolfram Burgard, Dieter Fox, Ken Fishkin, and Matthai Philipose. Mapping and localization with rfid technology. In *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. 2004*, pages 1015–1020. IEEE, 2004.

[134] Po Yang, Wenyan Wu, Mansour Moniri, and Claude C Chibelushi. Efficient object localization using sparsely distributed passive rfid tags. *IEEE Transactions on Industrial Electronics*, 11(12):5914–5924, 2013.

[135] Po Yang and Wenyan Wu. Efficient particle filter localization algorithm in dense passive rfid tag environment. *IEEE Transactions on Industrial Electronics*, 11(10):5641–5651, 2014.

[136] Nicholas Hanssens, Ajay Kulkarni, Rattapoom Tuchida, and Tyler Horton. Building agent-based intelligent workspaces. In *International Conference on Internet Computing*, volume 7, pages 675–681. Citeseer, 2002.

[137] Elisa Morganti, Leonardo Angelini, Andrea Adami, Denis Lalanne, Leandro Lorenzelli, and Elena Mugellini. A smart watch with embedded sensors to recognize objects, grasps and forearm gestures. *Procedia Engineering*, 7: 1169–1175, 2012.

[138] Tushar Chouhan, Ankit Panse, Anvesh Kumar Voona, and SM Sameer. Smart glove with gesture recognition ability for the hearing and speech impaired. In *2014 IEEE Global Humanitarian Technology Conference - South Asia Satellite (GHTC-SAS)*, pages 105–110. IEEE, 2014.

[139] Xiaomin Li, Di Li, Jiafu Wan, Athanasios V. Vasilakos, Chin-Feng Lai, and Shiyong Wang. A review of industrial wireless networks in the context of industry 4.0. *Wireless Networks*, 23(1):23–41, Jan 2017. ISSN 1572-8196. doi: 10.1007/s11276-015-1133-7. URL `https://doi.org/10.1007/s11276-015-1133-7`.

[140] Hyuenbo Cho. An intelligent workstation controller for computer-integrated manufacturing. 165:1–165, 1994.

[141] Michael S Ryoo, Kristen Grauman, and Jake K Aggarwal. A task-driven intelligent workspace system to provide guidance feedback. *Computer Vision and Image Understanding*, 15(5):520–534, 2010.

[142] Michael Kruppa, Lübomira Spassova, and Michael Schmitz. The virtual room inhabitant–intuitive interaction with intelligent environments. In *Australasian Joint Conference on Artificial Intelligence*, volume 10, pages 225–234. Springer, 2005.

[143] David B. Kaber, Carlene M. Perry, Noa Segall, Christopher K. McClernon, and Lawrence J. Prinzel III. Situation awareness implications of adaptive automation for information processing in an air traffic control-related task. *International Journal of Industrial Ergonomics*, 16:447–462, 2006.

[144] M.S. Ryoo, Kristen Grauman, and J.K. Aggarwal. A task-driven intelligent workspace system to provide guidance feedback. *Computer Vision and Image Understanding*, 114(5):520–534, 2010. ISSN 1077-3142. doi: https://doi.org/10.1016/j.cviu.2009.12.009. URL `http://www.sciencedirect.com/science/article/pii/S107731421000024X`.

[145] C. Perera, C. H. Liu, and S. Jayawardena. The emerging internet of things marketplace from an industrial perspective: A survey. *IEEE Transactions on Emerging Topics in Computing*, 14(4):585–598, Dec 2015. ISSN 2168-6750. doi: 10.1109/TETC.2015.2390034.

[146] Jianing Sun, Minglei Gao, Qifeng Wang, Minjie Jiang, Xuan Zhang, and Robert Schmitt. Smart services for enhancing personal competence in

industrie 4.0 digital factory. *Logforum*, 8(1):51–57, 2018. URL http://www.logforum.net/14_1_5_18.pdf.

[147] Marek Obitko and Václav Jirkovský. Big data semantics in industry 4.0. In *Industrial Applications of Holonic and Multi-Agent Systems*, pages 217–229. Springer International Publishing, 2015. ISBN 978-3-319-22867-9.

[148] AGCO. AGCO innovations in manufacturing with glass. https://news.agcocorp.com/topics/agco-innovations-in-manufacturing-with-glass, 2017. [Online; accessed 06-July-2018].

[149] Yongxin Liao, Fernando Deschamps, Eduardo de Freitas Rocha Loures, and Luiz Felipe Pierin Ramos. Past, present and future of industry 4.0 - a systematic literature review and research agenda proposal. *International Journal of Production Research*, 55(12):3609–3629, 2017. doi: 10.1080/00207543.2017.1308576.

[150] Sotiris Makris, Panagiotis Karagiannis, Spyridon Koukas, and Aleksandros-Stereos Matthaiakis. Augmented reality system for operator support in human–robot collaborative assembly. *CIRP Annals*, 4(1):61–64, 2016. ISSN 0007-8506. doi: https://doi.org/10.1016/j.cirp.2016.04.038. URL http://www.sciencedirect.com/science/article/pii/S0007850616300385.

[151] Marie Chan, Daniel Estève, Jean-Yves Fourniols, Christophe Escriba, and Eric Campo. Smart wearable systems: Current status and future challenges. *Artificial Intelligence in Medicine*, 20(3):137–156, 2012. ISSN 0933-3657. doi: https://doi.org/10.1016/j.artmed.2012.09.003. URL http://www.sciencedirect.com/science/article/pii/S0933365712001182.

[152] Geoff Appelboom, Elvis Camacho, Mickey E. Abraham, Samuel S. Bruce, Emmanuel LP Dumont, Brad E. Zacharia, Randy D'Amico, Justin Slomian, Jean Yves Reginster, Olivier Bruyère, and E. Sander Connolly. Smart wearable body sensors for patient self-assessment and monitoring. *Archives*

of Public Health, 72(1):28–37, Aug 2014. ISSN 2049-3258. doi: 10.1186/2049-3258-72-28. URL https://doi.org/10.1186/2049-3258-72-28.

[153] Gunasekaran Manogaran, Chandu Thota, Daphne Lopez, and Revathi Sundarasekar. *Big Data Security Intelligence for Healthcare Industry 4.0*, volume 24, pages 103–126. Springer International Publishing, 2017. ISBN 978-3-319-50660-9. doi: 10.1007/978-3-319-50660-9_5. URL https://doi.org/10.1007/978-3-319-50660-9_5.

[154] Enrico G. Caldarola, Gianfranco E. Modoni, and Marco. Sacco. A Knowledge-based Approach to Enhance the Workforce Skills and Competences within the Industry 4.0. In *Conference: eKNOW 2018 : The Tenth International Conference on Information, Process, and Knowledge Management*, Rome, Italy, 2018. IARIA XPS Press. ISBN 978-1-61208-620-0.

[155] Steven Miller. Ai: Augmentation, more so than automation. *Asian Management Insight*, 20(1):1–20, 2018. ISSN 2315-4284. URL http://ink.library.smu.edu.sg/ami/83.

[156] Kai Klinker, Lisa Berkemeier, Benedikt Zobel, Hanna Wüller, Veronika Huck-Fries, Manuel Wiesche, Hartmut Remmers, Oliver Thomas, and Helmut Krcmar. Structure for innovations: A use case taxonomy for smart glasses in service processes. In *Multikonferenz Wirtschaftsinformatik*, volume 12, pages 1599–1610, 2018.

[157] DHL. Augmented reality in logistics. http://www.dhl.com/content/dam/downloads/g0/about_us/logistics_insights/csi_augmented_reality_report_290414.pdf, 2014. [Online; accessed 20-July-2018].

[158] Michael Spitzer, Ibrahim Nanic, and Martin Ebner. Distance learning and assistance using smart glasses. *Education Sciences*, 8(1):1–8, 2018. ISSN 2227-7102. doi: 10.3390/educsci8010021. URL http://www.mdpi.com/2227-7102/8/1/21.

[159] Yuqiuge Hao and Petri Helo. The role of wearable devices in meeting the needs of cloud manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing*, 45:168–179, 2017. ISSN 0736-5845. doi: https://doi.org/10.1016/j.rcim.2015.10.001.

[160] Edwing Isaac Mejia Orozco and Cristian Javier Luciano. *Introduction to Haptics*, pages 141–151. Springer, 2018. ISBN 978-3-319-75582-3. doi: https://doi.org/10.1007/978-3-319-75583-0_11.

[161] P. Garrec, J. P. Friconneau, Y. Measson, and Y. Perrot. Able, an innovative transparent exoskeleton for the upper-limb. In *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1483–1488, Sept 2008. doi: 10.1109/IROS.2008.4651012. URL `https://hal-cea.archives-ouvertes.fr/cea-01588401`.

[162] Johan van der Vorm, Rachel Nugent, and Leonard O'Sullivan. Safety and risk management in designing for the lifecycle of an exoskeleton: A novel process developed in the robo-mate project. *Procedia Manufacturing*, 3: 1410–1417, 2015. ISSN 2351-9789. doi: https://doi.org/10.1016/j.promfg.2015.07.304. URL `http://www.sciencedirect.com/science/article/pii/S2351978915003054`. 6th International Conference on Applied Human Factors and Ergonomics (AHFE 2015) and the Affiliated Conferences.

[163] Abhishek Seth, Judy M. Vance, and James H. Oliver. Virtual reality for assembly methods prototyping: a review. *Virtual Reality*, 15(1):5–20, Mar 2011. ISSN 1434-9957. doi: 10.1007/s10055-009-0153-y. URL `https://doi.org/10.1007/s10055-009-0153-y`.

[164] Paulo Leitão, Armando Walter Colombo, and Stamatis Karnouskos. Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Computers in Industry*, 81:11–25, 2016. ISSN 0166-3615. doi: https://doi.org/10.1016/j.compind.2015.08.004. URL `http://www.sciencedirect.com/science/article/pii/S0166361515300348`.

[165] Trevor Richardson, Stephen B. Gilbert, Joseph Holub, Frederick Thompson, Anastacia MacAllister, Rafael Radkowski, Eliot Winer, and Boeing Company. Fusing self-reported and sensor data from mixed-reality training. *Industrial and Manufacturing Systems Engineering Conference Proceedings and Posters*, 12:1–12, 2014. URL `https://lib.dr.iastate.edu/imse_conf/92`.

[166] Mauricio Araujo Frigo, Ethel Cristina Chiari da Silva, and Gustavo Franco Barbosa. Augmented reality in aerospace manufacturing: A review. *Journal of Industrial and Intelligent Information*, 4(2):125–130, 2016. doi: 10.18178/jiii.4.2.125-130. URL `http://www.logforum.net/14_1_5_18.pdf`.

[167] Wilhelm Bauer, Sebastian Schlund, Tim Hornung, and Sven Schuler. Digitalization of industrial value chains – a review and evaluation of existing use cases of industry 4.0 in germany. *Scientific Journal of Logistics*, 14(3): 331–340, 2018.

[168] Bopaya Bidanda, Poonsiri Ariyawongrat, Kim LaScola Needy, Bryan A Norman, and Wipawee Tharmmaphornphilas. Human related issues in manufacturing cell design, implementation, and operation: a review and survey. *Computers & Industrial Engineering*, 48(3):507–523, 2005.

[169] Alina Roitberg, Alexander Perzylo, Nikhil Somani, Manuel Giuliani, Markus Rickert, and Alois Knoll. Human activity recognition in the context of industrial human-robot interaction. In *Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific*, volume 10, pages 1–10. IEEE, 2014.

[170] WD Timmons, HJ Chizeck, F Casas, V Chankong, and PG Katona. Parameter-constrained adaptive control. *Industrial & Engineering Chemistry Research*, 36(11):4894–4905, 1997.

[171] N. S. Ong. Activity-based cost tables to support wire harness design. *International Journal of Production Economics*, 29(3):271–289, 1993. ISSN 09255273. doi: 10.1016/0925-5273(93)90033-H.

[172] NS Ong and G Boothroyd. Assembly times for electrical connections and wire harnesses. *The International Journal of Advanced Manufacturing Technology*, 6(2):155–179, 1991.

[173] Joseph Bukchin and Michal Tzur. Design of flexible assembly line to minimize equipment cost. *IIE Transactions (Institute of Industrial Engineers)*, 32(7):585–598, 2000. ISSN 15458830. doi: 10.1080/07408170008967418.

[174] B R Sarker, H Pan, Br Sarker, and H Pan. Designing a Mixed-Model, Open-Station Assembly Line Using Mixed-Integer Programming. *The Journal of the Operational Research Society Palgrave Macmillan Journals*, 52(52):545–558, 2001.

[175] Assembly line conveyor systems. the photo was taken from pacline.com, 2015. URL `https://www.pacline.com/photos/photos-by-solution/\assembly-line-conveyors/`. [Online; accessed 22-February-2018].

[176] Catherine Da Cunha, Bruno Agard, and Andrew Kusiak. Design for Cost: Module-Based Mass Customization. *IEEE Transactions on Automation Science and Engineering*, 4(3):350–359, 2007. doi: 10.1109/TASE.2006.887160>. URL `https://hal.archives-ouvertes.fr/hal-00229758`.

[177] R Faragher and Ramsey Faragher. An analysis of the accuracy of bluetooth low energy for indoor positioning applications. 10:201–210, 2014.

[178] Sinan Gezici, Zhi Tian, Georgios B. Giannakis, Hisashi Kobayashi, Andreas F. Molisch, H. Vincent Poor, and Zafer Sahinoglu. Localization via ultra-wideband radios: A look at positioning aspects of future sensor networks. *IEEE Signal Processing Magazine*, 2005. ISSN 10535888. doi: 10.1109/MSP.2005.1458289.

[179] Abdulrahman Alarifi, AbdulMalik Al-Salman, Mansour Alsaleh, Ahmad Al-nafessah, Suheer Al-Hadhrami, Mai A Al-Ammar, and Hend S Al-Khalifa. Ultra wideband indoor positioning technologies: Analysis and recent advances. *Sensors*, 16(5):1–16, 2016.

[180] SJ Ingram, D Harmer, and M Quinlan. Ultra wideband indoor positioning systems and their use in emergencies. In *Position Location and Navigation Symposium, 2004. PLANS 2004*, volume 10, pages 706–715. IEEE, 2004.

[181] Zhiguo Lai, Harshit Joshi, Dennis Goeckel, Divi Gupta, Dev Gupta, and Abbie Mathew. Performance of uwb systems in the presence of severe multipath and narrowband interference. In *Ultra-Wideband, 2008. ICUWB 2008. IEEE International Conference on*, volume 4, pages 85–88. IEEE, 2008.

[182] Thomas Gigl, Gerard JM Janssen, Vedran Dizdarevic, Klaus Witrisal, and Zoubir Irahhauten. Analysis of a uwb indoor positioning system based on received signal strength. In *Positioning, Navigation and Communication, 2007. WPNC'07. 4th Workshop on*, pages 97–101. IEEE, 2007.

[183] Michael Cunningham, Paul Higgins, and Jim Browne. A Decision Support Tool for Planning Bills of Material. *Production Planning & Control*, 7(3): 312–328, 1996.

[184] Chao Wang, Henry Quesada-Pineda, D. Earl Kline, and Urs Buehlmann. Using Value Stream Mapping to Analyze an Upholstery Furniture Engineering Process. *Forest Products Journal*, 61(5):411–421, 2011. ISSN 0015-7473. doi: 10.13073/0015-7473-61.5.411.

[185] Fei Tao, Ying Zuo, Li Da Xu, Lin Lv, and Lin Zhang. Internet of things and BOM-Based life cycle assessment of energy-saving and emission-reduction of products. *IEEE Transactions on Industrial Informatics*, 10(2):1252–1261, 2014. ISSN 15513203. doi: 10.1109/TII.2014.2306771.

[186] Jitendra R Raol. *Multi-sensor data fusion with MATLAB®*. CRC Press, 2009.

[187] X Rong Li, Yunmin Zhu, Jie Wang, and Chongzhao Han. Optimal linear estimation fusion. i. unified fusion rules. *IEEE Transactions on Information Theory*, 49(9):2192–2208, 2003.

[188] Peter C Young. *Recursive estimation and time-series analysis: an introduction*. Springer Science & Business Media, 2012.

[189] Cameron M Crowe. Recursive identification of gross errors in linear data reconciliation. *AIChE Journal*, 34(4):541–550, 1988.

[190] Hongwei Tong and Cameron M Crowe. Detection of gross erros in data reconciliation by principal component analysis. *AIChE Journal*, 41(7):1712–1722, 1995.

[191] Frits K Pil and Matthias Holweg. Linking product variety to order-fulfillment strategies. *Interfaces*, 34(5):394–403, 2004.

[192] Dirk Van Goubergen and Hendrik Van Landeghem. Rules for integrating fast changeover capabilities into new equipment design. *Robotics and computer-integrated manufacturing*, 18(3-4):205–214, 2002.

[193] Christopher Ketelsen, Rasmus Andersen, Kjeld Nielsen, Ann-Louise Andersen, Thomas D. Brunoe, and Sofie Bech. A literature review on human changeover ability in high-variety production. In Ilkyeong Moon, Gyu M. Lee, Jinwoo Park, Dimitris Kiritsis, and Gregor von Cieminski, editors, *Advances in Production Management Systems. Smart Manufacturing for Industry 4.0*, pages 442–448, Cham, 2018. Springer International Publishing.

[194] Xiaorui Tong. *Anomaly Identification in Multistage Manufacturing Process using Peer Comparison of Product Inspection Metrics*. PhD thesis, University of Cincinnati, 2013.

[195] Adam Sanders, Chola Elangeswaran, and Jens Wulfsberg. Industry 4.0 implies lean manufacturing: research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management*, 9(3):811–833, 2016.

[196] Andrew P Dillon and Shigeo Shingo. *A revolution in manufacturing: the SMED system*. CRC Press, 1985.

[197] Iris Bento da Silva and Moacir Godinho Filho. Single-minute exchange of die (smed): a state-of-the-art literature review. *The International Journal of Advanced Manufacturing Technology*, pages 1–19, 2019.

[198] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

[199] Narsingh Deo. *Graph theory with applications to engineering and computer science*. Courier Dover Publications, 2017.

[200] Maurizio Faccio, Yuval Cohen, M Bevilacqua, FE Ciarapica, I De Sanctis, G Mazzuto, and C Paciarotti. A changeover time reduction through an integration of lean practices: a case study from pharmaceutical sector. *Assembly Automation*, 2015.

[201] Izabela Kutschenreiter-Praszkiewicz. Machine learning in smed. *Journal of Machine Engineering*, 18, 2018.

[202] Janos Abonyi, Tibor Kulcsar, Miklos Balaton, and Laszlo Nagy. Energy monitoring of process systems: time-series segmentation-based targeting models. *Clean Technologies and Environmental Policy*, 16(7):1245–1253, 2014.

[203] Keith J Moss. *Energy Management in Buildings*. Taylor & Francis, 2006.

[204] Dan Hou, Shuai Shao, Yun Zhang, Su Ling Liu, Yu Chen, and Shu Shen Zhang. Exergy analysis of a thermal power plant using a modeling approach. *Clean Technologies and Environmental Policy*, 14(5):805–813, 2012.

[205] Mohammed Ali Almomani, Mohammed Aladeemy, Abdelhakim Abdelhadi, and Ahmad Mumani. A proposed approach for setup time reduction through integrating conventional smed method with multiple criteria decision-making techniques. *Computers & Industrial Engineering*, 66(2):461–469, 2013.

[206] Lyle Robert Turner. *Production structure models and applications within a Statistical Activity Cost Theory (SACT) Framework*. PhD thesis, Queensland University of Technology, 2007.

[207] Tamas Ruppert and Janos Abonyi. Software sensor for activity-time monitoring and fault detection in production lines. *Sensors*, 18(7):2346, 2018.

[208] Tamás Ruppert, Szilárd Jaskó, Tibor Holczinger, and János Abonyi. Enabling technologies for operator 4.0: A survey. *Applied Sciences*, 8(9):1650, 2018.

[209] Tamas Ruppert, Gyula Dorgo, and Janos Abonyi. Fuzzy activity time-based model predictive control of open-station assembly lines. *Journal of Manufacturing Systems*, 54:12–23, 2020.

[210] Sarah Lacny, Todd Wilson, Fiona Clement, Derek J Roberts, Peter Faris, William A Ghali, and Deborah A Marshall. Kaplan–meier survival analysis overestimates cumulative incidence of health-related events in competing risk settings: a meta-analysis. *Journal of clinical epidemiology*, 93:25–35, 2018.

[211] Mark Stevenson and IVABS EpiCentre. An introduction to survival analysis. *EpiCentre, IVABS, Massey University*, 2009.

[212] Ritesh Ramchandani, Dianne M Finkelstein, and David A Schoenfeld. Estimation for an accelerated failure time model with intermediate states as auxiliary information. *Lifetime data analysis*, pages 1–20, 2018.

[213] Krishnamoorthi Sivalingam, Marco Sepulveda, Mark Spring, and Peter Davies. A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In *2018 2nd International Conference on Green Energy and Applications (ICGEA)*, pages 197–204. IEEE, 2018.

[214] Siddhartha Asthana, Pushpendra Singh, and Parul Gupta. Survival analysis: Objective assessment of wait time in hci. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 367–376. ACM, 2015.

[215] Robert J Batt and Santiago Gallino. The effects of searching and learning on pick-worker performance. *History*, 2017.

[216] Werner Bruggeman, Sr Anderson, and Y Levant. Modeling logistics costs using time-driven abc: a case in a distribution company. *Conceptual Paper and Case Study*, 2005.

[217] Boudewijn F Van Dongen, Ana Karla A de Medeiros, HMW Verbeek, AJMM Weijters, and Wil MP Van Der Aalst. The prom framework: A new era in process mining tool support. *26th International Concerence on Application and Theory of Petri Nets and Other Models of Concurrency (ICATPN 2005), June 20-25, 2005, Miami, FL, USA*, 2005:444–454, 2005.

[218] David G Kleinbaum and Mitchel Klein. *Survival analysis*, volume 3. Springer, 2010.

[219] Despina Koletsi and Nikolaos Pandis. Survival analysis, part 2: Kaplan-meier method and the log-rank test. *American journal of orthodontics and dentofacial orthopedics*, 152(4):569–571, 2017.

[220] Sunhee Park and David J Hendry. Reassessing schoenfeld residual tests of proportional hazards in political science event history analyses. *American Journal of Political Science*, 59(4):1072–1087, 2015.

[221] Frank E Harrell. Cox proportional hazards regression model. In *Regression modeling strategies*, pages 475–519. Springer, 2015.

[222] Rodrigo Romero-Silva, Erika Marsillac, Sabry Shaaban, and Margarita Hurtado-Hernández. Serial production line performance under random variation: Dealing with the 'law of variability'. *Journal of Manufacturing Systems*, 50:278 – 289, 2019. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2019.01.005.

[223] Chester G Gingrich, Daniel R Kuespert, and Thomas J McAvoy. Modeling human operators using neural networks. *ISA transactions*, 31(3):81–90, 1992.

[224] Daniel Leitold, Agnes Vathy-Fogarassy, and J. Abonyi. Empirical working time distribution-based line balancing with integrated simulated annealing

and dynamic programming. *Central European Journal of Operations Research*, 1 2018. ISSN 1435-246X. doi: 10.1007/s10100-018-0570-7.

[225] Gabriel Lodewijks. Two Decades Dynamics of Belt Conveyor Systems. *Bulk Solids Handling*, 22(2):124–132, 2002.

[226] Joaquín Bautista and Jaime Cano. Minimizing work overload in mixed-model assembly lines. *International Journal of Production Economics*, 112 (1):177–191, 2008. ISSN 09255273. doi: 10.1016/j.ijpe.2006.08.019.

[227] Tamás Ruppert and János Abonyi. Worker movement diagram based stochastic model of open paced conveyors. *Hungarian Journal of Industry and Chemistry*, 46(2):55–62, 2018.

[228] Tamas Ruppert and Janos Abonyi. Industrial internet of things based cycle time control of assembly lines. In *Future IoT Technologies (Future IoT), 2018 IEEE International Conference on*, volume 1, pages 1–4. IEEE, 2018.

[229] Fred N Silverman and John C Carter. A cost-based methodology for stochastic line balancing with intermittent line stoppages. *Management Science*, 32(4):455–463, 1986.

[230] E Erel*, I Sabuncuoglu, and H Sekerci. Stochastic assembly line balancing using beam search. *International Journal of Production Research*, 43(7): 1411–1426, 2005.

[231] Johannes Fisel, Yannick Exner, Nicole Stricker, and Gisela Lanza. Changeability and flexibility of assembly line balancing as a multi-objective optimization problem. *Journal of Manufacturing Systems*, 53:150 – 158, 2019. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2019.09.012.

[232] C. Kahraman. *Fuzzy Applications in Industrial Engineering.* Studies in Fuzziness and Soft Computing. Springer Berlin Heidelberg, 2007. ISBN 9783540335177.

[233] Arnold Kaufmann and Madan M. Gupta. *Fuzzy Mathematical Models in Engineering and Management Science.* Elsevier Science Inc., New York, NY, USA, 1988. ISBN 0444705015.

[234] M. F. Yang, Y. T. Chou, M. C. Lo, and W.C. Tseng. Applying fuzzy time distribution in pert model. In *Proceedings of the International MultiConference of Engineers and Computer Scientists 2014*, volume 2, pages 1084–1087. IMECS, 2014.

[235] F Habibi, O Birgani, H Koppelaar, and S Radenović. Using fuzzy logic to improve the project time and cost estimation based on project evaluation and review technique (pert). *Journal of Project Management*, 3(4):183–196, 2018.

[236] Yasuhiro Tsujimura, Mitsuo Gen, and Erika Kubota. Solving fuzzy assembly-line balancing problem with genetic algorithms. *Computers & Industrial Engineering*, 29(1):543 – 547, 1995. ISSN 0360-8352. doi: https://doi.org/10.1016/0360-8352(95)00131-J. Proceedings of the 17th International Conference on Computers and Industrial Engineering.

[237] A. Ghaleb, M. Heshmat, M. A. El-Sharief, and M. G. El-Sebaie. Using fuzzy logic and discrete event simulation to enhance production lines performance: Case study. In *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)*, pages 653–657, April 2019. doi: 10.1109/IEA.2019.8714887.

[238] M. Duran Toksari and Oğuzhan Ahmet Arık. Single machine scheduling problems under position-dependent fuzzy learning effect with fuzzy processing times. *Journal of Manufacturing Systems*, 45:159 – 179, 2017. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2017.08.006.

[239] Azriel Rosenfeld. Fuzzy groups. *Journal of mathematical analysis and applications*, 35(3):512–517, 1971.

[240] Janos Abonyi. *Fuzzy Model Identification for Control.* Birkhouser, 2003.

[241] Thiago Cantos Lopes, Adalberto Sato Michels, Celso Gustavo Stall Sikora, and Leandro Magatão. Balancing and cyclical scheduling of asynchronous mixed-model assembly lines with parallel stations. *Journal of Manufacturing Systems*, 50:193 – 200, 2019. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2019.01.001.

[242] M. Assid, A. Gharbi, and A. Hajji. Production and setup control policy for unreliable hybrid manufacturing-remanufacturing systems. *Journal of Manufacturing Systems*, 50:103 – 118, 2019. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2018.12.004.

[243] J. Mukund Nilakantan, George Q. Huang, and S.G. Ponnambalam. An investigation on minimizing cycle time and total energy consumption in robotic assembly line systems. *Journal of Cleaner Production*, 90:311 – 325, 2015. ISSN 0959-6526. doi: https://doi.org/10.1016/j.jclepro.2014.11.041.

[244] Neda Manavizadeh, Masoud Rabbani, and Farzad Radmehr. A new multi-objective approach in order to balancing and sequencing u-shaped mixed model assembly line problem: a proposed heuristic algorithm. *The International Journal of Advanced Manufacturing Technology*, 79(1):415–425, Jul 2015. ISSN 1433-3015. doi: 10.1007/s00170-015-6841-8.

[245] Jenny L. Diaz C. and Carlos Ocampo-Martinez. Energy efficiency in discrete-manufacturing systems: Insights, trends, and control strategies. *Journal of Manufacturing Systems*, 52:131 – 145, 2019. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2019.05.002.

[246] Yashar Zeinaly, Bart De Schutter, and Hans Hellendoorn. A model predictive control approach for the line balancing in baggage handling systems. *IFAC Proceedings Volumes*, 45(24):215–220, 2012.

[247] Martin W Braun, Daniel E Rivera, ME Flores, W Matthew Carlyle, and Karl G Kempf. A model predictive control framework for robust management of multi-product, multi-echelon demand networks. *Annual Reviews in Control*, 27(2):229–245, 2003.

[248] Bart De Schutter and Ton Van Den Boom. Model predictive control for max-plus-linear discrete event systems. *Automatica*, 37(7):1049–1056, 2001.

[249] Stanimir Mollov, Robert Babuska, Janos Abonyi, and Henk B Verbruggen. Effective optimization for fuzzy model predictive control. *IEEE Transactions on fuzzy systems*, 12(5):661–675, 2004.

[250] João Miguel da Costa Sousa and Uzay Kaymak. Model predictive control using fuzzy decision functions. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 31(1):54–65, 2001.

[251] Tamás Ruppert, Gergely Honti, and János Abonyi. Multilayer network-based production flow analysis. *Complexity*, 2018:1–15, 2018.

[252] Witold Pedrycz, Andrzej Skowron, and Vladik Kreinovich. *Handbook of granular computing*. John Wiley & Sons, 2008.

[253] Didier Dubois and Henri Prade. Processing fuzzy temporal knowledge. *IEEE Transactions on Systems, Man, and Cybernetics*, 19(4):729–744, 1989.

[254] Li-Hui Tsai. Mixed-model sequencing to minimize utility work and the risk of conveyor stoppage. *Management Science*, 41(3):485–495, 1995.

[255] Armin Scholl and Christian Becker. State-of-the-art exact and heuristic solution procedures for simple assembly line balancing. *European Journal of Operational Research*, 168(3):666–693, 2006.

Publications related to theses

T. Ruppert and J. Abonyi, “Software sensor for activity-time monitoring and fault detection in production lines,” *Sensors*, vol. 18, no. 7, p. 2346, 2018

T. Ruppert, S. Jaskó, T. Holczinger, and J. Abonyi, “Enabling technologies for operator 4.0: A survey,” *Applied Sciences*, vol. 8, no. 9, p. 1650, 2018

T. Ruppert, G. Dorgo, and J. Abonyi, “Fuzzy activity time-based model predictive control of open-station assembly lines,” *Journal of Manufacturing Systems*, vol. 54, pp. 12–23, 2020

T. Ruppert and J. Abonyi, “Industrial internet of things based cycle time control of assembly lines,” *Future IoT Technologies (Future IoT), 2018 IEEE International Conference on*, vol. 1, pp. 1–4, 2018

Further publications

T. Ruppert, G. Honti, and J. Abonyi, “Multilayer network-based production flow analysis,” *Complexity*, vol. 2018, pp. 1–15, 2018

T. Ruppert and J. Abonyi, “Worker movement diagram based stochastic model of open paced conveyors,” *Hungarian Journal of Industry and Chemistry*, vol. 46, no. 2, pp. 55–62, 2018

D. Csereklei, T. Ruppert, and J. Abonyi, “Digitális iker a gyártási folyamat optimalizációban,” *Műszaki Kémiai Napok 2019*, p. 20

T.-a. Tran, M. Daróczi, J. Abonyi, and T. Ruppert, “Optimizing resources assignment folr balancing modular production line,” *The 9th International Conference on Management*, p. 162, 2019