Enabling Technologies for Operator 4.0: A Survey

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Received: 31 July 2018; Accepted: 7 September 2018; Published: 13 September 2018

Abstract: 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 multi-purpose 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.

Keywords: Operator 4.0; Industry 4.0; Internet of Things (IoT); Human-Cyber-Physical Systems (H-CPS); intelligent workspace; intelligent space; IPS; RFID

1. Introduction

The continuous innovations of Cyber-Physical Systems (CPS), the Internet of Things (IoT), the Internet of Services (IoS), robotics, big data, cloud and cognitive computing and augmented reality (AR) result in significant change in production systems [1,2]. 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 [3–5]. The approach of China is also based on the most modern IT technologies [6] that are not only used to improve the efficiency of the production, but also to share manufacturing capacity and support cooperation [7]. The U.S. has introduced “reindustrialization” policies to reinvigorate its manufacturing industry. By releasing the “New Robot Strategy,” Japan is attempting to accelerate the development of cooperative robots and unmanned plants to revolutionize the robot industry, cope with the aggravation of Japanese social and economic issues and enhance international competitiveness. The “New Industrial France“, the “high-value manufacturing” strategy of the U.K. and the “advanced innovators’ strategy” of South Korea have similar CPS-based focus points [8]. 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 [9]. 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 [10,11] and
assess the Industry 4.0 maturity of industrial enterprises in the domain of discrete manufacturing [12]. Thanks to the fast and flexible communications between CPSs, smart sensors and actuators, real-time and self-controlled operations can be realized [6,13]. The new smart IoT devices have the potential to design mobile machines that replace human minds [14]. Researchers at Oxford University estimated that approximately 47% of all U.S. 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 [15,16].

Although the increase in the degree of automation reduces costs and improves productivity [17], human operators are still essential elements of manufacturing systems [18,19]. The increasing degree of automation also does not necessarily lead to enhanced operator performance [20]. Handling human factors is a challenging problem concerning both cellular manufacturing [21] and human-robot interaction [22]. For example, smart factories have to take into consideration operators who are aging or apprentices by using advanced technologies to help people to integrate into the modern manufacturing workforce [23].

Industry 4.0 (especially IoT devices and CPS) allows new types of interactions between operators and machines [24]. 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 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-CPSs) designed to facilitate cooperation between humans and machines [25].

Although the state of the art in the area of Industry 4.0 has been reviewed recently [3] and systematic literature reviews are frequently published [26–28], there is a need to study how 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.

This paper 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 Operator 4.0 solutions proposed by Romero et al. [23,25].

The paper 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 is proposed in Section 2. The required infrastructural background is presented in the remaining sections. The IoT solution for tracking operator activities is introduced in Section 3, while IoT-based solutions developed to support operator activities by providing feedback are summarized in Section 4. Conclusions and recommendations based on the review are proposed in Section 5.

2. 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. The Operator 4.0 Concept and Human-Cyber-Physical Systems

The Operator 4.0 typology depicts how the technologies of the fourth industrial revolution will assist the work of operators [25]. 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. This human-robot collaboration in the industrial environment is a fascinating field with a specific focus on physical and cognitive interaction [29]. 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 [25] (see Figure 1).

The main elements of the Operator 4.0 methodology are explained in Table 1. Analytical operator-type solutions utilize big data analytics to collect, organize and analyze large datasets [23]. 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.

![Figure 1. (R)evolution of the tasks of operators in manufacturing systems.](image)

**Table 1.** Elements of the Operator 4.0 methodology according to [23,25].

| 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 [30,31]. |
| Augmented operator   | Augmented Reality (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 [32–34]. Spatial AR projectors support automotive manufacturing [35–37]. |
| Collaborative operator | Collaborative robots (CoBots) are designed to work in direct cooperation with operators to perform repetitive and non-ergonomic tasks. | Rethink-Robotics with Baxter and Sawyer promises low-cost and easy-to-use collaborative robots [38]. |
| 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 [23]. Military-based applications can predict potentially problematic situations before they arise [23]. |
| 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 [39]. |
| 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 [40]. |
| 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 [41]. |
| 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 it. | Provide the users with an environment to explore the outcomes of their decisions without putting themselves or the environment at risk [42]. The Virtual Reality (VR)-based gait training program provides real-time feedback [43]. |
|                      | Multi-purpose virtual engineering space [44]. |
With 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 [45–47]. How these principles should be applied during the development process is presented in Table 2.

Table 2. Design principles of Industry 4.0 applied to Operator 4.0 solutions.

| Design principle       | Description                                                                 | Application          |
|------------------------|-----------------------------------------------------------------------------|----------------------|
| System integration     | It combines subsystems into one system. Vertical integration connects manufacturing systems and technologies [48]; horizontal integration connects functions and data across the value chain [49]. | Analytical operator  |
| Modularity             | It is important for the ability of the manufacturing system to adapt to continuous changes [50–52]. | Augmented operator  |
| Interoperability       | It allows human resources, smart products and smart factories to connect, communicate and operate together [50]. 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 [53].               | Smarter operator     |
| Decentralization       | It is based on the distributive approach, where the system consists of autonomous parts, which can act independently [50]. It simplifies the structure of the system, which simplifies the planning and coordination of processes and increases the reliability [54]. | Social operator      |
| Corporate social       | It involves environmental and labor regulations.                             | Social operator      |
| responsibility         |                                                                             |                      |
| Virtualization         | It uses a digital twin, i.e., all data from the physical world are presented in a cyber-physical model [55]. | Virtual operator     |

The Operator 4.0 concept aims to create Human-Cyber-Physical Production Systems (H-CPPS) that improve the abilities of the operators [23]. 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, but handling uncertainty and the stochastic nature are difficult. Adaptive systems are suitable to handle these problems with the help of more frequent monitoring and model adaptation functions [56–59]. 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 [60]. To support this goal, an overview concerning the elements of CPS from the perspective of operators is given in Table 3, and the levels of CPSs with a description of the functions and tasks are presented in Figure 2.

As tasks should be transformed into a form that computers can understand, task analysis is becoming more and more crucial due to the difficulties of the externalization of the tacit knowledge of the operators [61]. Tacit knowledge contains all cognitive skills and technical know-how that are challenging to articulate [62,63]. Without elicit tacit knowledge, the chance of losing critical information and best practice is very high [64]. Hierarchical task analysis extended with the ‘skill, rule and knowledge’ framework can capture tacit knowledge [65], an approach which has been proven to be useful in manufacturing [66]. 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 a robot that can replace the operator [67]. The modeling of the physical reality and realizing it in the CPS are critical tasks [68–71].

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 [72] and emotions [73] associated with the decisions and operator actions.
Sensors and feedback technologies of the 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.

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

Figure 2. Architecture of cyber-physical systems.

Table 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 [74,75] |
|             | Self-adjust                                   |                                                                 |
|             | Self-configure                                |                                                                 |
| Cognition   | Collaborative diagnostic and decision-making | Virtual Reality (VR) [76–78]                                   |
|             | Remote visualization for humans               | Augmented Reality (AR) [79–81]                                 |
| Cyber       | Digital twin                                  | Decision-making based on a digital twin [82–84]                |
|             | Model of operator                             | Worker-movement diagram [85–88]                                |
|             |                                              | Monte Carlo simulation of a stochastic process model [89,90]   |
| Conversion  | Smart analytics                               | Online performance monitoring based on sensor fusion [91,92]   |
|             | Degradation and performance prediction         |                                                                 |
| Connection  | Sensor network                                | Wearable tracker [93,94]                                       |
|             |                                               | Indoor positioning system [95–99]                               |

2.2. 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 [100]. 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 [101] where an intelligent Space (iSpace) system has been designed for the virtual and physical support of people and mobile robots [102]. Intelligent interaction space supports the operators to complete their work with high efficiency, high success rate and low burden [103]. The iSpace framework is shown in Figure 3.
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Figure 3. Intelligent Space (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 4. The design of connections between resources, users and tasks is the key to the design of intelligent interaction space.

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 [102]. The acquired information is transmitted via a wireless network and processed by dedicated computers, so any
event involving or a change in the monitored parameters inside the space is carefully analyzed and processed [105].

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 [106].

3. IoT-Based Solutions for Operator Activity Tracking

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) [13], it is necessary to overview what kinds of tools are available for monitoring the activity of the operators.

Usually, operator activity is monitored by Radio Frequency IDentification (RFID)-based object tracking [107]. This technology can collect real-time data about the activities of workers (operators) and machines, as well as movements of materials [108] and workpieces [109,110]. Multi-agent supported RFID systems realize location-sensing systems [111] and intelligent-guided view systems [112]. RFID systems for human-activity monitoring provide an excellent opportunity to observe the work of the operators [113]. 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, as well as real-time data for OEE (Overall Equipment Effectiveness) calculations provided [114].

The tracking of production can be significantly improved by the Indoor Positioning System (IPS) utilized for localizing the positions of the products and operators [95]. The applications of IPS and its potential benefits in terms of process development are compiled in Table 4.

Context-aware systems require unobtrusive sensors to track each step of the performed task [115]. As wearable sensors are becoming more common, their utilization is also becoming more attractive [116]. However, hand motion-based activity recognition is still challenging [117] and requires the application of advanced machine learning algorithms [118]. 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 [119]. How all these smart sensor-based IoT technologies can be used to design Operator 4.0-type solutions is compiled in Table 5.

| Application Area | Description | Examples |
|------------------|-------------|----------|
| Performance monitoring | Measure effects of process development and Business Process Reengineering (BPR). | Analyze moving- and staying-time of operators [120]. |
| Movement analysis | Spaghetti diagram of operator movement to reduce unnecessary movement and optimize the layout and supply chain. | Reduce the duration of material handling [121]. Reduce the number of unnecessary movements of operators [120]. Support real-time Manufacturing Execution Systems (MES) [122]. |
| Support 5S workplace organization methodology projects | Track tools and optimize the place of application and storage. | Decrease of stock and scrap. Improve activity times [120]. |
| 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 [123]. |
Table 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 [102]                                       |
|                      | Olfactory sensors    | Electronic nose [124]                                                   |
| Augmented operator   | Microphones          | Machine vision systems for quality inspection [126,127]                 |
| Virtual operator     | Visual sensors       | Image processing, e.g., panoramic images [128], create the environment of virtual reality [129] |
|                      |                      | Smart camera for probabilistic tracking [130]                           |
| Collaborative operator | Localization sensors | IPS in manufacturing [95] and hybrid locating systems [131]               |
| Social operator      |                      | Smart and social factories based on the connection between machines, products and humans [135] |
| Smarter and healthy operator | Wearable sensors | The smart glove maps the orientation of the hand and fingers with the help of bend sensors [137] |

4. IoT-Based Solutions to Support Operator Activities

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 [93] and communication [138] solutions help to handle this challenge. The previous section 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 [60].

In the early applications, the production activities required to complete orders were scheduled and managed by Shop Floor Control Systems (SFCS). In [139], a hierarchical SFCS (shop, workstation, equipment) was adopted. In [140], 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 [141].

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 [142]. Visual collaboration systems can provide appropriate instructions for each step of the assembly task [140]. 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 [143]. 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 the types of devices presented in Table 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 [144].

The connections between the categories of Operator 4.0 solutions and potential feedback technologies are shown in Table 6. Which feedback opportunity is expedient is defined by the task in question. For example, in the case of the 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.

**Table 6. Feedback technologies for Operator 4.0 solutions.**

| Operator 4.0       | Feedback                                      | Technologies                                                                 | Examples                                                                 |
|-------------------|-----------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------|
| Analytical        | Report/potential danger                       | Smart glasses, smartphones, tablets and personal displays                     | Big data-based development of a manufacturing process [145].             |
| Augmented         | Each possible feedback                        | Smart glasses                                                               | AR for tractor manufacturing [146]. Smart glasses [23,26].               |
| Collaborative     | Waiting for interaction/technical problem     | Smart glasses, smartphones, tablets, personal displays, headsets and        | Collaborative operator workspace [147].                                  |
| Healthy           | Need rest                                     | Smart glasses, smartphones, tablets, personal displays and headsets          | Measurement of physiological parameters [148,149]. Security issues [150].|
| Smarter           | Answer to a question                          | Smart glasses, smartphones, tablets, personal displays and headsets          | Chatbot [151] and AI provide support to operators [152].                |
| Social            | Emergency                                     | Smart glasses, smartphones, tablets, personal displays and headsets          | Facebook-based product avatar [40] and Social Manufacturing (SocialM) [53].|
|                   | Process                                       | Smart glasses, smartphones, tablets, personal displays and headsets          | Facebook-based product avatar [40] and Social Manufacturing (SocialM) [53].|
|                   | Manufacturing                                  | Smart glasses, smartphones, tablets, personal displays and headsets          | Facebook-based product avatar [40] and Social Manufacturing (SocialM) [53].|
|                   | Technical information                          | Smart glasses, smartphones, tablets, personal displays and headsets          | Facebook-based product avatar [40] and Social Manufacturing (SocialM) [53].|
| Super-strength    | Optimal route/targeting/training              | Smart glasses, tablets and smartphones                                      | Navigation [153,154] and targeting [154–156].                           |
|                   | Force feedback on a hand or whole arm         | Smart gloves and special exoskeletons                                       | HaptX [157,158], VRgluv [159] and ABLEProject [41,160] are such technologies. |
|                   | Danger indicator                               | Smart glasses and speakers                                                   | Safety and risk management (related to exoskeleton technology) [161].     |
| Virtual operator  | Collision/weight/pressure                     | Smart clothes/smart gloves                                                   | VR technology in prototyping and testing [162]. This kind of technology becomes more efficient with every wearable feedback device (e.g., smart gloves [163]) that use (secondary) human senses directly. |

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 [146]. 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)
- 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 [154]. Ten workers who used smart glasses for three weeks managed to
distribute 20,000 packages (9000 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. The 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; however, 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 [164,165].

These benefits are in accordance with what was observed in the introduction of general Industry 4.0 solutions [166]. 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 are 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, as well, but it is difficult to compensate due to the high investment and development costs of these technologies.

5. Conclusions

This paper 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. [23,25], the 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 a 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 work, the architecture and infrastructure of Operator 4.0 technologies were surveyed. Monitoring and data-driven analytics are the key to process development [26,138]. 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.
Author Contributions: T.H., S.J. and T.R. prepared the original draft, J.A. created the concept and reviewed and edited the manuscript.

Funding: This research was supported by the National Research, Development and Innovation Office (NKFIH) through the project OTKA-116674 (Process mining and deep learning in the natural sciences and process development) and Széchenyi 2020 under EFOP-3.6.1-16-2016-00015 Smart Specialization Strategy (S3) Comprehensive Institutional Development Program.

Conflicts of Interest: The authors declare that there is no conflict of interest with regard to the publication of this paper.

Abbreviations

The following abbreviations are used in this manuscript:

5S Workplace organization methodology
ABC Activity-Based Costing
AI Artificial Intelligence
AM Additive Manufacturing
AR Augmented Reality
BPR Business Process Reengineering
CNC Computer Numerical Control
CoBot Collaborative Robot
CPS Cyber-Physical System
CPPS Cyber-Physical Production System
CS Computer Science
DIND Distributed Intelligent Network Device
E-SNS Enterprise Social Networking Service
H-CPS Human-Cyber-Physical System
H-CPPS Human-Cyber-Physical Production System
HITL Human-In-The-loop
HMI Human Machine Interface
ICT Information and Communication Technologies
IoT Internet of Things
IoS Internet of Services
IPA Intelligent Personal Assistant
IPS Indoor Positioning System
iSpace Intelligent Space
KPI Key Performance Indicator
MaaS Manufacturing as a Service
MBI Model-Based Instructions
MES Manufacturing Execution System
MEMS Micro-Electro Mechanical System
MST Manufacturing Science and Technology
OEE Overall Equipment Effectiveness
Paas Product-as-a-Service
PwC PricewaterhouseCoopers
RFID Radio Frequency Identification
SFC Shop Floor Control
SFCS Shop Floor Control System
UWB Ultra-Wideband
VR Virtual Reality

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