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An overview on human-centred technologies, measurements and optimisation in assembly systems

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ABSTRACT

This paper offers an in-depth examination of the ergonomics of human-centred assembly systems in Industry 4.0, where manual tasks remain essential. The use of advanced technologies such as motion capture (MOCAP) and virtual reality (VR) is analysed as ways to enhance system efficiency and improve worker well-being. The paper highlights the importance of optimising assembly system performance while considering both economic and human factors. Metrics to assess ergonomic risk and productivity are discussed based on human-centred technologies, and existing operational research models are explored to analyse how human factors could be considered in optimising system performance. Additionally, the paper explores potential future directions and how they could play a role in Industry 4.0.

KEYWORDS

Human factors; motion capture; ergonomics and productivity; assembly systems; optimisation

1. Introduction

Industry 4.0 and, more recently, Industry 5.0 strongly emphasise human factors, recognising the crucial role that human skills, knowledge, and experience play in the performed work. Through the use of advanced technologies that allow motion capture and data analysis, Industry 5.0 should enable improvements in the assembly systems and the work environments ergonomic, creating a truly collaborative relationship between humans and machines (Nahavandi 2019). These technologies enable real-time monitoring and adjusting machine performance, ensuring safe and comfortable working conditions for workers. Harnessing data from Industry 5.0 technologies can thus optimise the production process and improve worker well-being (Ivanov 2022).

Nowadays, more than ever, decision-makers consider the social and ethical implications of technologies seeking to grant the best balance between productivity/system efficiency and human well-being (A. Otto et al. 2017).

Industrial assembly processes can be very complex regarding variability and uncertainty of some components' quality, delivery delays or machines operations (Bortolini et al. 2020).

Minimising the ergonomic risks gains in attention for managers at assembly line factories, especially in light of the ageing working population in several countries (Peng and Chan 2020). Numerous case studies: A. Otto

et al. (2017), Bortolini et al. (2020), and Simonetto, Arena, and Peron (2022) have pointed a clear connection between the assembly line quality, the inadequate workplace ergonomic and the way the operator moves in his space (Manghisi et al. 2017). To measure the ergonomic levels of an assembly line operator and analyse his movements, the use of technologies is crucial (Donisi et al. 2022). To acquire data on posture and movement, 'motion capture' technologies are mainly and widely used (Bortolini et al. 2020).

The existing literature on human factors continues to grow due to increasing concerns and new regulations on working conditions. In previous work, Slama et al. (2022) proposed a preliminary literature review on the human-centred assembly/disassembly systems by focussing on technologies (used to capture human motion), metrics (used to assess human ergonomic risks and productivity) and operational research models (used to optimise the performance system). The lack of a harmonised framework for assembly systems was pointed out.

The current work extends this preliminary analysis with a more in-depth investigation while expanding the database-reviewed studies. The main objective of this research is to provide interested practitioners with a comprehensive view and insightful toolkit for modelling human characteristics, both from the perspective of human motion capture technologies and optimisation

models from operations research. The following research questions are addressed throughout this paper: (i) What are the human factors and Ergonomics studied in the literature, and how are they modelled in assembly systems? (ii) Which technologies are used to capture and measure human factors? and (iii) How are the human-aware modelling frameworks integrated into optimisation models, and how does their integration affect the models from a mathematical programming perspective?

Our investigation of these questions infers research gaps and highlights research opportunities. This paper is motivated by the lack of existing works bringing together the different blocks necessary for optimal production in human-centred assembly systems. To the best of our knowledge, this is the first state-of-the-art paper to present a literature review of the layers involved in the assembly optimisation process, considering human factors.

The main contributions of this paper are to provide:

- A deep description and a detailed comparison of the available ‘motion analysis’ technologies. We added a review of articles combining virtual reality and digital twins and MOCAP as a possibility to track operator movements,
- An extensive review of the most-used ‘human factors and productivity’ measurements using MOCAP technologies. We discuss their need for different assembly case studies and the main differences and trends in their use,
- A detailed taxonomy of existing research considering human factors in optimisation. We distinguish mainly three optimisation problem categories: (i) Assembly Line Balancing (ALB), (ii) Assembly Line Balancing with Human-Robot Collaboration (ALB-HRC) and (iii) Job Rotation Scheduling (JRS),
- An exhaustive discussion of the reviewed works is proposed. We analyse the reviewed papers and propose possible improvements. As future direction and considering the outcome of our analysis, we propose an ‘iterative framework’ taking advantage of various elements, like the worker and workstation constraints, the real acquired measurements, a new index that combines various human factors and ergonomic needs and the possibility of updating the optimisation solution depending on any external or internal constraints.

The structure of our paper is as follows: In Section 2, the terminology behind our paper and related previous review articles are introduced. In Section 3, we present the selection criteria and the methodology used to collect reviewed records. In Section 4, the technologies used in assembly systems for human movement detection and

acquisition are reported and discussed. In Section 5, we report different measurements computed from data acquired by MOCAP systems. Both the measurements of ergonomics and productivity are pointed out and discussed. In Section 6, optimisation models, resulting from operational research for solving assembly systems, are split into the main problems (ALB, ALB-HRC, JRS). In all these studies, human factors are present as a constraint or objective. Section 7 gives all our observations on the studied works. Besides, future directions are pointed out, and a new framework is proposed. In the last Section 8, conclusions regarding this work are reported.

2. Review of previous literature

The current review is contextualised and justified in light of the literature on Human-centred optimisation assembly systems. Firstly, we briefly explain some key concepts used in this work. Then, we summarise the pertinent reviews already published in this field. We suggest precisely defining the review of the essential items corresponding to our study selection criteria.

As this topic is likely the subject of transdisciplinary work, it is essential to foster understanding between diverse academic and professional scholars and practitioners. The scientific literature has key human factors and ergonomics terms with various interpretations and definitions. When analysing human factors-sensitive optimisation and decision support problems, we think it is advantageous for the operations research community to employ explicit terminologies.

In the following, we report the main human-related key concepts based on the work of Prunet et al. (2022a, 2022b), Stecke and Mokhtarzadeh (2022), Vijayakumar et al. (2022), and Czaja et al. (2019):

- Human factors and ergonomics are defined by the International Ergonomics Association as being
the profession of applying theory, principles, data, and methods to design to optimise human well-being and overall system performance. Human factors and ergonomics is a scientific discipline that focuses on understanding interactions among humans and other system elements. Ergonomics, human engineering, and human factors engineering are other names for it (IEA 2023).
- Human aspects refers to studying how people interact with technology, systems, and products, considering user needs, abilities, and limitations. This can include evaluating the design of products, systems, and environments from a human perspective and determining how these factors can impact usability, productivity, and safety (Czaja et al. 2019).

- Human-aware modelling refers to using models to simulate human behaviour and performance in a specific context, such as in the design of a new product or system. These models can predict how a user will interact with a particular design and identify potential issues that may arise (Prunet et al. 2022a).
- Ergonomic risk refers to the likelihood of injury or harm to a person due to exposure to specific working conditions or environments. This can include repetitive or repeated motions, prolonged static postures, high-force exertions, and vibrations (Stecke and Mokhtarzadeh 2022).
- Risk factors refer to the specific conditions or characteristics that can increase the likelihood of injury or harm. These can include things like the poor design of products and systems, inadequate training, and lack of proper equipment or tools. The identification of risk factors is essential for the design of interventions and the prevention of work-related injuries and illnesses (Stecke and Mokhtarzadeh 2022).
- Operator productivity can be evaluated by how effectively an operator moves around their work environment, how quickly they complete tasks, and how well they utilise their physical resources (such as tools and equipment) (Vijayakumar et al. 2022).

Including human factors in optimisation issues is a broad topic that applies to many assembly systems and can be approached from various angles. As a result, numerous reviews and surveys on the subject have been released. These works, however, frequently concentrate on a single topic (assembly systems) but with a scope that goes beyond simple optimisation issues. An overview of the reviews that are most pertinent to the context of the current work is given in this section. The relevance and position of our work within this body of literature are then highlighted.

In Katirae et al. (2021) and Prunet et al. (2022a), authors give a systematic assessment of the literature that concentrated on studies that took into account and integrated workforce differences in models linked to issues with assembly line balancing, work/worker assignment, job rotation, and workstation/layout design. Regarding Motion Capture in industrial applications, Menolotto et al. (2020) enumerate various MOCAP solutions in industrial environments and present the sectors that primarily benefit from them. Authors identify the most targeted areas as well as the advantages and limitations of using these technologies. For the ALB problem, although the majority of studies in literature contribute to the design of manual assembly lines (Aguilar, García-Villoria, and Pastor 2020; Boyesen, Schulze, and Scholl 2021), ergonomics-focused

approaches are few and far between. A. Otto and Battaia (2017), Xu and Hall (2021), and Hashemi-Petroodi et al. (2021) provide an overview of the subsequently released literature in this area. More recently, Tropschuh, Cegarra, and Battaia (2023) provided a practical-oriented overview for including physiological and mental aspects in existing employee scheduling.

3. Methodology

This study aims to provide a recent overview of human-centred technologies, measurements and optimisation models in assembly systems. A particular interest is given to papers that integrate these three layers to improve the assembly systems are of particular interest.

To circumscribe our study, we selected only articles crossing the following five keyword criteria:

- (1) *Assembly systems*: An assembly system is a collection of equipment, tools, and processes to assemble individual parts or components to create a finished product. This can include manual assembly stations, automated assembly lines, and various types of machinery and robotics. Assembly systems are used in various industries, from manufacturing to construction, and can vary greatly in complexity and size (Ghandi and Masehian 2015). Assembly systems are widely studied in the literature. In this paper, we consider mainly three assembly related ancillary activities: Assembly Line Balancing (ALB), Assembly Line Balancing with Human-Robot Collaboration (ALB-HRC), and Job Rotation Scheduling (JRS).
- (2) *Human-centred technologies*: Only studies employing the different measurements computed from data acquired by MOCAP systems are considered in this paper.
- (3) *Human-centred measurement*: Reviewed papers should employ the measurement of ergonomic risk techniques in assembly systems. Both measurements of ergonomics and productivity in assembly systems will be discussed.
- (4) *Human factors and ergonomics*. Here, we focus only on studies dealing with the modelling of human aspects or the improvement of the ergonomic work environment.
- (5) *Optimisation*. Only papers suggesting optimisation models and their conceptual frameworks and modelling programs are considered in this review.

Figure 1 illustrates the various layers considered in this review.

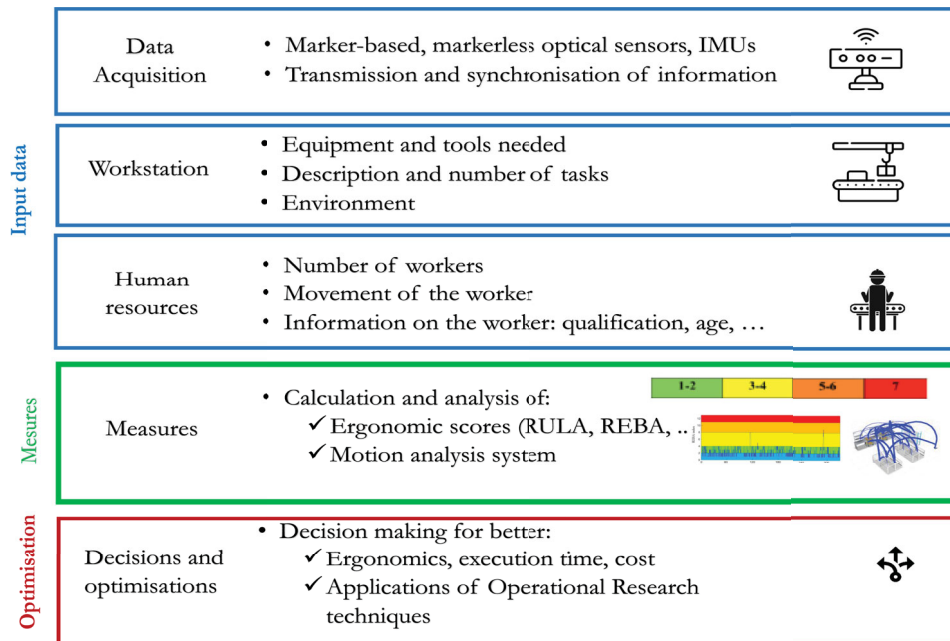


Figure 1. A human-centred assembly system main layers for best real case study optimisation process.

In the following, the methodology indicates how material and related works have been collected to enrich our papers database.

The material is collected using Scopus and Web of Science databases by applying the following set of rules:

- All publication dates are from 2013 to 2020.
- Only papers published in English are considered.
- Only journal papers, book chapters and conference proceedings are considered.
- We select a set of categories on the Web of Science. This set, noted by 'WC' in the query, is presented in Table 2.
- According to the scope of this review, four sets of keywords are created: (i) words related to optimisation, (ii) words related to operations research, (iii) a set to specify that we are only interested in assembly systems, and (iv) one for human factors. All the words defining the sets are given in Table 1, and the queries launched on Scopus and Web of Science are available in Table 2.

The initial queries (see Table 2) produced 181 records. These records were then screened based on the titles, keywords, and abstracts to determine their relevance to the study. As a result, some articles were excluded as they did not meet the specified inclusion criteria, leaving us with 123 articles. To enhance the comprehensiveness of our research, we expanded our search by examining the reference lists of the more relevant papers. This additional screening process yielded 100 more records that were considered relevant to the study. Consequently, the total number of included studies increased to 223. In

Table 1. Used keywords in the papers selection process.

A = Optimisation	optim*, minimi*, maximi*
B = Operations Research	'objective model', 'Linear program*', 'heuristic*', 'Exact method*', 'Exact algorithm*', 'Approximation Algorithm*', 'Approximation Approach', 'Approximation method*', 'decision-making', 'Non?Linear' and metaheuristic*
B = Manufacturing systems	Assembl*
C = Human factors	'Human Factor*', 'Ergonomic*', Workforce*, Musculoskeletal, 'Human Motion*', Posture*, Equity, 'Energy Expenditure*', Vibration et Exposure, Motion*, Health, 'Motion Analys*', 'Movement Analys*', 'Inertial Measur*', Acceleromet*, 'Sensing Solution*', 'Tracking System*', 'Motion Tracking', 'Motion Capture', 'Acquisition System*', MOCAP*, IMU*, 'Optical Sensor*', Camera*, 'Virtual Reality', 'Augmented Reality', Sensor*

the final stage of our assessment, we carefully evaluated all 223 records, eliminating duplicate entries and removing less eligible papers that fell outside the scope of our study. This rigorous evaluation led to the inclusion of 113 studies that met all the necessary criteria for our research.

Figure 2 displays the results of a cartographic analysis using VOSviewer. The frequent keywords in the analysed articles are shown. As depicted in Figure 3, most of the selected papers fall under the intersection of Operations Research, Engineering, Computer Science, Automation, and Management Science.

As seen in Figure 4, there has been a growing interest in studying human factors in assembly systems, as shown by increased publications over the years.

Table 2. Search queries in databases.

Database	Search query
Web of Science	TS = ((optim* OR minimi* OR maximi*) AND ('objective model' OR 'Linear program*' OR 'heuristic*' OR 'Exact method*' OR 'Exact algorithm*' OR 'Approximation Algorithm*' OR 'Approximation Approach' OR 'Approximation method*' OR 'decision-making' OR 'Non?Linear' OR metaheuristic*) AND (Assembl*) AND ('Human Factor*' OR 'Ergonomic*' OR Workforce* OR Musculoskeletal OR 'Human Motion*' OR Posture* OR Equity OR 'Energy Expenditure*' OR (Vibration AND Exposure) OR Motion* OR Health OR 'Motion Analys*' OR 'Movement Analys*' OR 'Inertial Measur*' OR Acceleromet* OR 'Sensing Solution*' OR 'Tracking System*' OR 'Motion Tracking' OR 'Motion Capture' OR 'Acquisition System*' OR MOCAP* OR IMU* OR 'Optical Sensor*' OR Camera* OR 'Virtual Reality' OR 'Augmented Reality' OR Sensor*)) AND WC = ('Engineering Manufacturing' OR 'Engineering Industrial' OR 'Operations Research Management Science' OR 'Automation Control Systems' OR 'Computer Science Interdisciplinary Applications' OR 'Robotics' OR 'Computer Science Artificial Intelligence' OR 'Engineering Mechanical' OR 'Engineering Electrical Electronic' OR 'Ergonomics' OR 'Management') AND PY = (2013–2023)
Scopus	TITLE-ABS-KEY (optim* OR minimi* OR maximi*) AND TITLE-ABS-KEY ('objective model' OR 'Linear program*' OR 'heuristic*' OR 'Exact method*' OR 'Exact algorithm*' OR 'Approximation Algorithm*' OR 'Approximation Approach' OR 'Approximation method*' OR 'decision-making' OR 'Non?Linear' OR metaheuristic*) AND TITLE-ABS-KEY (Assembl*) AND TITLE-ABS-KEY ('Human Factor*' OR 'Ergonomic*' OR Workforce* OR Musculoskeletal OR 'Human Motion*' OR Posture* OR Equity OR 'Energy Expenditure*' OR (Vibration AND Exposure) OR Motion* OR Health OR 'Motion Analys*' OR 'Movement Analys*' OR 'Inertial Measur*' OR Acceleromet* OR 'Sensing Solution*' OR 'Tracking System*' OR 'Motion Tracking' OR 'Motion Capture' OR 'Acquisition System*' OR MOCAP* OR IMU* OR 'Optical Sensor*' OR Camera* OR 'Virtual Reality' OR 'Augmented Reality' OR Sensor*)

4. Human-centred technologies

In manual assembly systems, which are focussed on human work, the main concern regards the movement of the operators either with each other or their work environment. These operators' movements must be precisely captured in time and space. Then, the raw motion data is filtered and processed to reveal physical or time-consuming constraints. The optimisation of these constraints allows the improvement of ergonomics and productivity. Tracking systems are the basic technology for reconstructing human posture and movements (Maurizio et al. 2019). Recently, industries have adopted MOCAP technology to record human movements. Menolotto et al. (2020) present a complete review of using MOCAP in industrial applications. Referring to Agethen, Otto, Mengel, et al. (2016), we distinguish two groups of this technology: Inertial Measurement Units and camera-based sensors. The different applicability degrees can be found in Ceseracciu, Sawacha, and Cobelli (2014). In recent studies, Colombo, Regazzoni, and Rizzi (2013),

optical, inertial, or both systems are commonly applied to acquire and analyse human motion.

In the industrial environment and the factory of the future concept, in particular, Jardim-Goncalves, Romero, and Grilo (2017), complex and non-repetitive tasks can be performed by operators to fit the personalised production paradigm. MOCAP technologies are of significant help for tracking the manual assembly processes either to capitalise on the operator's knowledge or to evaluate and improve their working conditions and ergonomics. The following will introduce and compare the main technologies related to motion capture systems and/or coupled with virtual reality.

4.1. Inertial measurement units

As reported by Ribeiro and Santos (2017), in Inertial Measurement Units (IMUs) technology, inertial sensors are miniaturised and placed on the human body parts as shown by Figure 5(a). this technology represents an electronic device that captures the body's specific measurements such as force, angular rate, and body orientation (see example on Figure 5(a)). Based on a combination of accelerometers, gyroscopes, and sometimes magnetometers, it provides relative position and orientation updates.

Recently, the company Xsens Technologies B.V. (Enschede, NL) released the MTw Awinda IMUs set-up. It consists of 17 wireless motion trackers (16 grams each, $47 \times 30 \times 13$ mm) coupled to a wireless dongle or data receiving station with patented wireless protocols enabling robust transmission even in industrial environments. The small size of the IMUs and the dedicated calibration of the whole set-up also enable accurate 'absolute displacement' measured from one base location. The location and fastening of the sensors on the body also cope with the movements and the eventual safety clothes worn by the operator. This system is now considered as ground truth for 'into the wild' motion capture, as it is also possible to 'leave' the base from 20 m (office) to 50 m (outdoor), and the motion capture engine is now immune to magnetism. Each IMU is synchronised at 10 μ s with respect to the other to obtain consistent overall measurements and so reduce any distortions (Palermo et al. 2022). Figure 5(a) shows the location of the full-body sensors, which can also be reduced to the upper or lower body, resulting in an acquisition frequency increase (from 60 Hz to 120 Hz).

4.2. Camera-marker-based sensors

This technology exploits active or passive markers properly placed in specific body parts. The position of

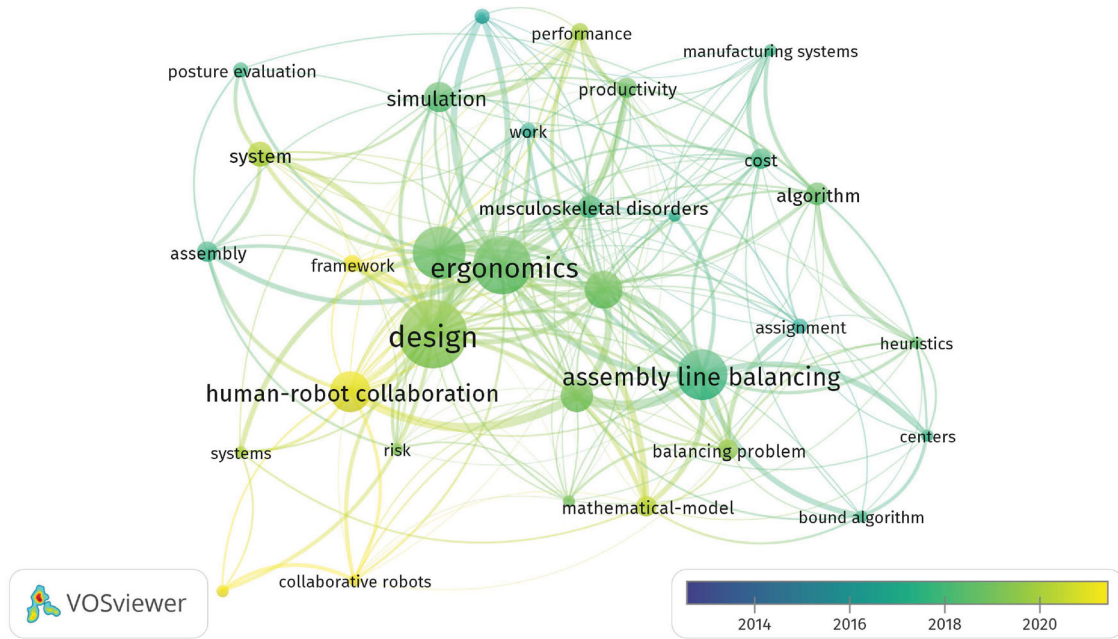


Figure 2. Frequently occurring keywords identified in the considered articles.

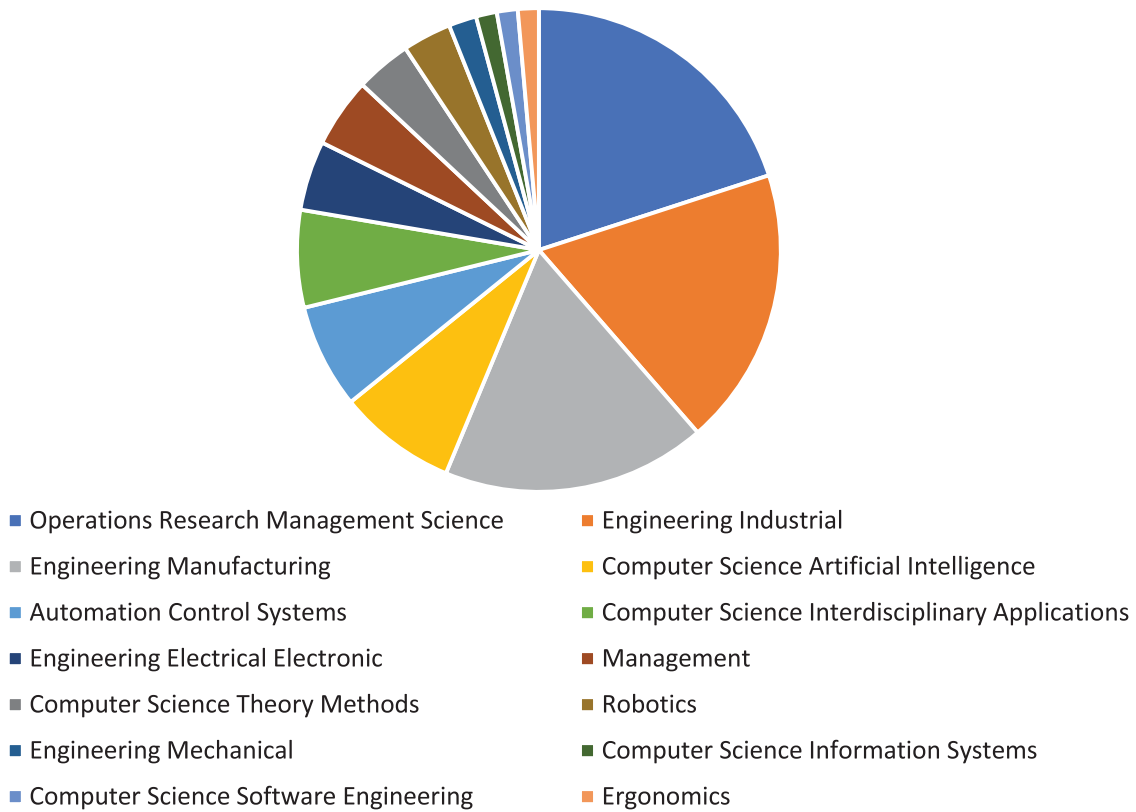


Figure 3. Number of publications by Web of Science Categories.

different markers is detected in the two-dimensional (2D) field of view from a bunch of cameras. However, the cameras' relative position and orientation enable us to triangulate the location of markers in the 3D space after appropriate calibration routines.

As suggested by Ceseracciu, Sawacha, and Cobelli (2014), we distinguish two sets of markers: active and passive. The first set is based on flashing infrared LEDs that emit their own light one by one at a high frequency driven by camera synchronisation. The second consists

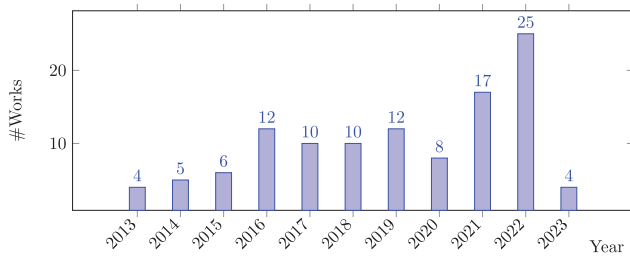


Figure 4. Distribution of the number of works per year.

of tiny plastic spheres with a retroreflective coating that reflect light from an infrared source surrounding the camera lens. As illustrated in Figure 5(b), this sensor requires equipping an operator with the markers and calibrating the MOCAP environment.

4.3. Camera-marker-less sensors

Camera-based off-the-shelf devices such as RGB, infrared and depth cameras (e.g. Microsoft Kinect, Xbox 360, Asus XTION and PrimeSense) were successfully employed for human motion tracking and posture estimation or action recognition (Castellano, Alvarez-Pastor, and Bradley 2014).

Human Pose Estimation involves extracting joint coordinates and constructing a human skeletal representation from images or videos. Desmarais et al. (2021) and Sarafianos et al. (2016) reviewed the pose estimation with either monocular or multi-view techniques and using static image or video inputs.

Recently, markerless depth cameras have been increasingly used in various industrial use cases (see for eg. Bortolini et al. 2020, 2018; Diego-Mas and Alcaide-Marzal 2014). These are based on a structured light or time-of-flight approach and can detect specific points of the human body to reconstruct its skeleton.

The Microsoft Kinect V1 and V2 (Wang et al. 2015) are the most popular depth cameras. V2 is the most recent

version (Diego-Mas and Alcaide-Marzal 2014) that uses time-of-flight technology. This latter is more accurate and enables the capture of 25 body joints. It is more robust to artificial illumination and sunlight but still not robust to occlusions. An assembly case study that uses a Kinect camera is presented in Bortolini et al. (2020) and Simonetto, Arena, and Peron (2022).

Recent markerless motion capture systems offer a compromise between accuracy and time expense. Besides, more and more suitable low-cost solutions are available for accurate and rapid data collection that can be used for postural ergonomic risk assessment in manufacturing systems.

Two different groups of markerless optical capture technologies can be noticed in literature: *RGB camera-based systems* and *Depth camera*. An example of successful extraction of 2D human pose information from the RGB-Camera data is detailed in Cao et al. (2017). The industrial system is also powerful among markerless systems (Kanko et al. 2021).

4.4. Virtual reality and digital twin

Virtual reality provides the possibility of creating virtual environments where human workers can interact with the virtual elements and also where the technologies, like cobots and mobile robots, can be modelled. This facilitates the study of the assembly systems. As a result of the virtual environment, different alternatives between the human workers and the technologies can be studied before their implementation in real workplaces (Havard et al. 2019). This helps to create optimal workplaces where technologies and human workers can interact with optimal results. There are several technologies used in virtual reality (Costa, Petry, and Moreira 2022), including:

- Head-Mounted Displays: Devices worn on the head, displaying the virtual environment to the user.



(a) M-Pose for location and placement of the full body inertial sensors using the guidelines set by XSens (placement for illustration only).



(b) Positioning of retro-reflective markers (10mm and 4mm in diameter, without and with flash) for studying the movements of the right arm.

Figure 5. Two motion capture systems: IMUs and camera-marker-based sensors.

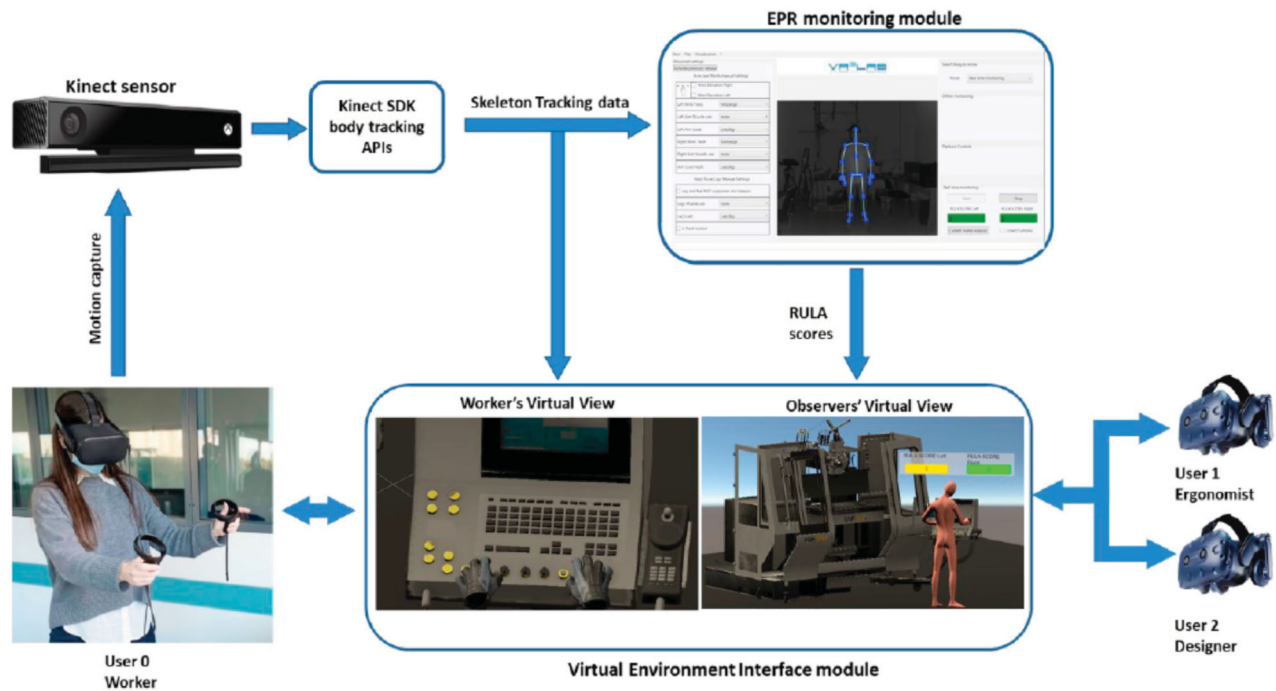


Figure 6. The ErgoVR tool proposed by Manghisi, Evangelista, and Uva (2022) for ergonomic postural risk assessment.

- Hand controllers: Devices allowing users to interact with the virtual environment naturally, such as by gesturing or pointing.
- Position tracking: This technology uses sensors to track the user's movements and adjust the virtual environment accordingly.
- Audio: Specialised headphones or speakers are used to create a realistic and immersive audio experience.
- Haptic feedback: This technology uses vibrations or other tactile sensations to simulate the feeling of touch in the virtual environment.
- Eye-tracking: this technology tracks the user's gaze to create realistic and immersive VR environments.
- 7.6DoF (Degrees of Freedom) Tracking: this technology tracks the user's head's and hand's location and orientation in 3D space.

Recently, the combination of MOCAP systems and virtual reality has emerged as a new type of workplace setup that offers numerous evaluations and assessments of human movements. This system is composed of two phases. First, the operator is immersed in a virtual environment through VR. Second, the operator is fitted with a MOCAP system that generates a digital copy of the operator, known as the digital twin, which accurately represents the operator's reality. The main advantage of this system is that it allows accurate measurements of human movements, such as ergonomic assessments, to be made on the digital twin, which has the same anthropometric data and performs the same movements.

Manghisi, Evangelista, and Uva (2022) developed a Virtual Reality-based multiplayer tool exploiting low-cost body tracking technology to evaluate ergonomic postural risk (see Figure 6). The tool allows evaluation both in real-time and offline the ergonomic postural risk according to the Rapid Upper Limb Assessment metrics (RULA). This tool, called ErgoVR, uses the Kinect V2 sensor body tracking functionalities and the HTC VIVE PRO Head Mounted Display (HMD) for data visualisation.

Evangelista et al. (2023) present an HMD-based application for Microsoft HoloLens 2, for monitoring ergonomic postural risk (EPR) in Augmented Reality (AR). This tool enables EPR assessment according to RULA metrics by allowing real-time monitoring of the operations performed by the worker at the workstation.

Using collaborative robots, Židek et al. (2021) proposed a methodology to develop a digital twin representation and assist the assembly process. Židek et al. (2021) developed an aircraft wing assembly case study where real workers hold real tools. More studies are attracted by the potentialities offered by the combined use of the MOCAP system and VR in assembly environments (Battini et al. 2018; Dallel et al. 2023; Michalos et al. 2018; Peruzzini, Carassai, and Pellicciari 2017).

Dolgui, Sgarbossa, and Simonetto (2022) gives a recent systematic literature review where both AR and VR are discussed regarding the advantages they can offer for operators in assembly systems.

4.5. Comparison of different sensors

Table 3 details a comparison between different sensor technologies. This table was first presented by Menolotto et al. (2020) and enriched by our recent analysis. In recent years, optical systems, in particular, have progressed enormously in applications in various fields, including now the possibility to be used underwater up to 40 m depth (e.g. Qualisys Arqus UW) with a range of 30 m for the detection of reflective markers.

The development of more sensitive and higher-resolution sensors allows for efficient coupling with powerful onboard stroboscopic lighting systems. This enables use in particularly harsh environments (strong light, dust, rain, etc.) with increased precision in both time and space. These goals are achieved using the latest technologies (superLED, optimised CMOS sensors, built-in onboard digital processing, etc.), but at the expense of the system's exploding cost. Marker-less systems have progressed on two different fronts, either by using high-resolution systems, close to marker-based, coupled with robust proprietary software (e.g. Theia3D), or by using

low-resolution systems at relatively low cost, or even ToF (Time of flight) systems (e.g. KinectV3 or so).

Some recent studies (e.g. Tang et al. 2022) compared the performance of markerless and marker-based systems and discussed the application of both systems to gait analysis. Marker-less systems can now even be applied to people wearing 'everyday' clothing and generate reproducible dynamic skeletal behaviour, the accuracy of which is directly related to image processing routines and acquisition configurations (quality and the number of cameras). Desmarais et al. (2021) has reviewed all proposed methods using this technology. The main disadvantage of MOCAP optical systems is the application 'into the wild' or manufacturing when strong occlusions occur. This is complemented by IMUs' systems that allow up to 50 m displacements from the acquisition base with impressive acquisition and measurement qualities (e.g. Xsens MTW Awinda). IMUs are more uncomfortable to wear and can sometimes interfere with the studied subject or impair the studied action, particularly with very light or soft tools due to IMUs' weight. For the same

Table 3. Motion capture systems and characteristics (from Menolotto et al. 2020, updated Jan2023).

Characteristics	Sensors		
	IMUs	Marker-Based	Camera-Based Marker-Less
Accuracy	High (0.75° to 1.5°) ^a	Very high (0.03 mm and 5.10 ⁻⁵) ^b	Low (dynamic, 30 Hz, 0.025 m), subject to distance from camera
Set up	Straightforward, subject to a number of IMUs	Requires frequent calibration (calibration time about 60 s for 20 m ^b –3 m high)	Checker-board or extrinsic calibration same as marker-based ^c
Capture volume	Distance of subject from station	Related to camera resolution and number (50 × 50 × 8 m)	Crossed field of view of high-resolution cameras (e.g. 8 × 8 × 3 m)
Cost of installation	From €50 to €15,000 for full body suit ^a	From €4000 to €200,000	From €200 to €30,000 ^d
Ease of use and data processing	Raw sensor data to ASCII files	Fully automated, including gap filling and skeletons, full 3D kinematics	Custom-made or industrial software (e.g. Theia3D)
Invasiveness (Individual)	Minimal	Medium (markers or Traqr attachment) ^f	Minimal
Invasiveness (workplace)	Minimal	High (typically from 6 to 12 cameras)	Medium to high (from 1 to 8 cameras)
Line of sight necessity	No	Yes	Yes
Portability	Yes, easily	Yes (with tripods, cables and cameras boxes)	Yes
Range	Wireless, 20–50 m from station	Up to 50 m camera to marker ^b	Up to 10m form cameras (Theia3D)
Sampling rate	Up to 300 Hz full-body wireless	Up to 1400 fps ^g	15–30 Hz or higher with high speed cameras
Software(€)	Usually bespoke or off-the-shelf software Cost €20,000	Off-the-shelf software, Cost €20,000 free or proprietary dongle	Usually bespoke or off-the-shelf software, Cost €20,000
Noise sources and environmental interference	High-temperature changes, compensated ferromagnetic exists	Vibrations, Extra Light compensated now	IR interference and vibrations
Other limitations	Small Drift	Cameras obstructions	Cameras obstructions, high contrast objects
MSD application	Yes	Yes	Yes
Collaborative with moving objects	Yes, with 'prop' supplementary IMU	Yes, with 6DoF tracking	Yes, with computer vision tracking
Synchronisation and triggering	Yes	Yes	Yes, for digital cameras

Notes: ^aBased on the specs of the Xsens MTW Awinda. and the Xsens MVN. ^bBased on 8 Qualisys Arqus26 cameras (6.5 MP, 290 fps). ^cTheia3D, Theia Markerless, Inc., Kingston, ON, Canada (Tang et al. 2022). ^dbased on Kinect V3. ^eBased on 8 Qualisys Miqus video. ^fBased on 6–10 Qualisys Traqr. ^gBased on Qualisys Arqus A5 in Hi speed mode.

Table 4. Comparison between main ergonomic methods used in assembly systems.

Method	Focus	Invested body segments	Feature
RULA ^a (Senjaya, Nugroho Yahya, and Lee 2022)	Posture, lifting tasks	Lower and upper limbs, spine	Q, L/F
REBA ^b (Hita-Gutiérrez et al. 2020)	Posture, lifting tasks	Lower and upper limbs, spine	Q, L/F
OCRA ^c (Tiacci and Mimmi 2018)	Posture	Upper limbs	Q, frequency, duration, recovery
QEC ^d (Widjajati, Islami, and Wahyudi 2021)	Posture	Upper body and limb	Static and dynamic tasks
NIOSH ^e (Song et al. 2016)	Lifting tasks	Spine	Q, L/F, frequency
EAWS ^f (M. Otto et al. 2019)	Posture	Lower and upper limbs, spine	Q, L/F, frequency, duration, recovery
OWAS ^g (Kee 2021)	Posture	Lower limbs, spine	Q, L/F

Notes: ^aRapid Upper Limb Assessment, ^bRapid Entire Body Assessment, ^cOccupational Repetitive Action, ^dQuick Exposure Check, ^eNational Institute for Occupational Safety and Health, ^fErgonomic Assessment Work Sheet, ^gOvako Working posture Assessment System, Q: Quantitative, L/F: Load/Force.

reasons, and even if recent solutions have been developed to measure hand and finger gestures with optoelectronic connected gloves, marker-based optical systems are still up to date for this kind of measurement with high 3D accuracy. The same kind of retro-reflective markers (e.g. semi-spherical, 3–5 mm of diameter) used for the fingers or face expressions can then be affixed on tiny tools for 6DoF (6 degrees of freedom, i.e. x - y - z translations and angular roll-pitch-yaw) simultaneous measurements.

5. Human-centred measurements

Recent technologies such as MOCAP and VR helped engineers develop systems that automatically measure operator ergonomics and productivity. Typically, ergonomic considerations encompass the assessment of operator posture, force exertion, and motion, with data analysis involving the application of statistical techniques to calculate a score. Recent works have been initiated to measure both operator ergonomic scores and productivity (Joshi and Deshpande 2019). In what follows, we focus on ergonomics and productivity measurements derived from analysing human movement in an assembly systems workspace.

5.1. Ergonomic viewpoint

Manual or semi-manual assembly work frequently involves repetitive actions, high levels of physical stress, and awkward postures. Recently, Battini, Persona, and Sgarbossa (2014) and Battini et al. (2017, 2016) have shown a connection between productivity and ergonomics for assembly lines, where including the ergonomics evaluations in the human operations analysis is a win-win strategy because of the interaction between productivity, motion efficiency, and operational safety.

Numerous methods for evaluating ergonomics have been developed, including self-assessment techniques and observational methods using video recordings or software tools to compute ergonomic indexes. Interested readers can refer to Joshi and Deshpande (2019) for a systematic review. In the last paper, the authors

identified several new measurements such as HARM, SWEA, NERPA, ALLA, PERA, WERA and SES. In the current review, a focus is given to ergonomic assessment measurements used by studies in assembly systems. Table 4 summarises their meaning and functions.

For example, OWAS, RULA, and REBA methods measure the angle of several skeleton joints and various body components to assess the operator's working posture (Gonçalves et al. 2022). The researchers concluded that the most popular ergonomic methods for minimising musculoskeletal risk associated with repetitive handling activities are OCRA, RULA, REBA, and QEC. In a recent paper (Ozdemir et al. 2021), the authors specify that the components' weight, size, and form might be considered as additional parameters to calculate employees' posture and determine ergonomic scores. Interested readers can refer to Kee (2022) for more details about these methods.

Several studies have been undertaken in recent years to include the ergonomic risk in the assembly line balancing issue (A. Otto and Battaia 2017; Campana, Iori, and Moreira 2022). Ergonomic risk assessment of assembly workers in the automobile sector is detailed in Ojha and Vinay (2015). They demonstrated the existence of a moderate to high risk of work-related musculoskeletal problems using RULA as an ergonomic measure. Chakravarthy, Subbaiah, and Shekar (2015) adopted OWAS and RULA methods in a car production assembly line and successfully categorised the activities as being in a 'yellow zone,' or a moderate risk zone. More recently, Cimen, Baykasoglu, and Akyol (2022) studied assembly systems and ergonomic risks in automotive parts manufacturing plants. The authors argued that, for ergonomic risk calculation, the method used is always justified by the type of the considered workstation. For example, in manual assembly lines, the calculation of the ergonomic risk is often based on the OCRA method since the assembly operations are made up of a set of repetitive gestures of the upper limbs.

In these studies, Bautista-Valhondo and Alfaro-Pozo (2018a), Bautista-Valhondo and Alfaro-Pozo (2018b), Bautista, Alfaro-Pozo, and Batalla-García (2016) and

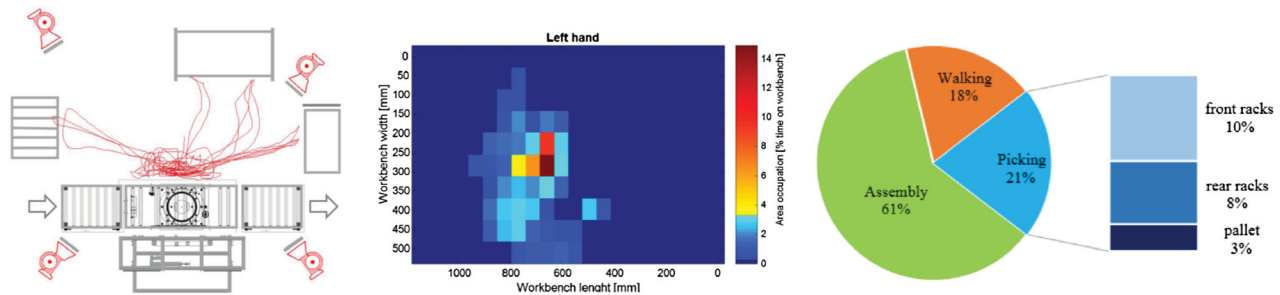


Figure 7. Examples of measurements from a productivity viewpoint. From left to right: operator walking path, distribution of hands on the workbench and time allocation among the various operator activities (Bortolini et al. 2020).

Michalos et al. (2018) ergonomic scores and measurements are considered in assembly systems. A recent survey is developed in Donisi et al. (2022).

5.2. Productivity point of view

Using MOCAP technologies, it is possible to measure operator ergonomic scores, but we can also take advantage of information about the operator's working performance.

A dynamic analysis of the operator's movements about the workspace layout where the tasks are carried out (component locations, workspace usage, manufacturing activities, task execution time, racks or workbench utilisation, hands position, etc.) can be used to evaluate the operator's productivity. The latter is evaluated based on operator tasks, body movements, and distances travelled across time and space (hands, feet, body, etc.).

Measurements of operator workplace considering space and time are and not only: job execution times, operator movement pathways, and time spent near workstation objects like machines, racks, shelves, and workbenches, hand displacement over time and velocity trend; cumulative vertical movements for lifting and lowering; Control volume analysis for differentiating between 'added-value' and 'non-added-value' operations Figure 7 shows some of these measurements' examples.

Ritt, Costa, and Miralles (2016) and Bortolini et al. (2021, 2020, 2018) present various contributions to measure worker productivity in time and space. In their latest work, they developed a Motion Analysis System (MAS) for operator body analysis while working in assembly processes. They proposed a specific configuration of markerless optical MOCAP in the workplace environment. Then, using this system, they evaluate operator assembly tasks from two perspectives: productivity and ergonomic viewpoints. From a productivity viewpoint, they measure hand displacement and velocity over time and velocity trend, cumulative vertical movements for lifting and lowering, and control volume analysis to distinguish between added-value and no-added-value

activities. Ferrari et al. (2018) proposes another MAS, where a network of MOCAP system is set up to evaluate the operator tasks automatically and to quantitatively measure his productivity performances based on a time and space analysis. Accordingly, they measure (i) the different paths travelled by the operators, (ii) the added value portion of the working time and the instant and frequency, and (iii) the duration of picking activities from each possible storage location of the shop floor.

Based on a distributed depth camera array, Agethen, Otto, Mengel, et al. (2016) proposed a novel tracking approach, being able to reconstruct operators' walk paths within an assembly line. Agethen, Otto, Mengel, et al. (2016) also proposed a novel tracking approach to measure the walk paths of operators in assembly lines and then detect non-value-adding tasks.

Recently, Simonetto, Arena, and Peron (2022) proposed to combine the Virtual Reality and MOCAP systems within a clear methodology to follow when designing assembly system workplaces. Their methodological framework is tested within a simple case study where ergonomics and productivity measurement encompasses the current ageing workforce scenario by explicitly including the ageing workforce's main characteristics (reduced flexibility and strength and greater experience of older operators). Similarly, Battini et al. (2018) investigated the potentialities of this design procedure. They proposed the so-called 'VR-Ergo Log system', an inertial motion capture system integrated with immersive reality and heart rate monitoring to include fatigue considerations in the productivity measurements.

It is widely known that the world population is ageing. Besides, the labour market is experiencing an ageing workforce due to the necessity of increasing the retirement age (Peng and Chan 2020). This represents a key issue in some industrial sectors, especially assembly systems and human-centred workplaces. In fact, repetitive movements are often required, and the decline of the operators' physical functions as the years go by (e.g. reduced musculoskeletal force, flexibility and motion

capability) certainly represents a threat; thus, it is essential to take these factors into account in both ergonomics and productivity measurements.

The ageing of the global population is a well-known trend. In addition, the workforce is getting older due to the need to raise the retirement age. In some industrial sectors, particularly assembly systems containing manual operations, this poses a serious problem (Peng and Chan 2020). Repetitive motions are often required, and as operators get older, their physical capabilities decline (e.g. diminished musculoskeletal force, flexibility, and motion capability). Therefore, it is crucial to consider these aspects in both ergonomics and productivity evaluations.

Wang and Abubakar (2017) and Di Pasquale et al. (2018) presented an interesting literature review on the impact of human factors on productivity performances, concluding that both experience and age are the most significant human factors in productivity measurements. The same conclusion is presented in the survey of Abubakar and Wang (2019) that confirms that experience is the most significant human factor affecting individual human performance. It has also been demonstrated that ageing affects productivity performance: at age 38, human employees' typical assembly times rise by an average of 1%. However, different results were observed by Roosaar, Masso, and Varblane (2019). They showed that older workers, thanks to their experience, remained at least as productive as their younger counterparts.

Besides ageing and experience, more human factors directly impact human performance and are revealed by productivity measurements such as Physical work capacity, gender, Learning and forgetting, and Circadian rhythms (Wang and Abubakar 2017).

5.3. Motion capture for productivity and ergonomics analysis

MOCAP systems can be used for different purposes in industry (Geiselhart, Otto, and Rukzio 2016). The current study focuses on their ability to measure operator ergonomics and productivity by tracking and analysing human movement patterns in assembly systems in real-time. Donisi et al. (2022) demonstrated that this information concerning operator movement can be used to identify areas where ergonomics can be improved, such as reducing repetitive motions and evaluating the efficiency of work processes. By tracking workers' movements and body posture, MOCAP systems can identify potential ergonomic risk factors, such as awkward postures or repetitive motions, and provide recommendations to improve the work environment. Additionally, by analysing the speed and accuracy of movements,

Table 5. Example of recent studies computing human-centred measurements using technologies in assembly systems.

Source	Technology	Human-centred Measurements
Nguyen et al. (2015)	DC	EAWS
Ojha and Vinay (2015)	RGB cameras	RULA
Agethen, Otto, Gaisbauer, et al. (2016)	DC	Walk path trajectories
Agethen, Otto, Mengel, et al. (2016)	DC	Walk path trajectories
Faccio et al. (2017)	DC	REBA and OWAS
Ferrari et al. (2018)	DC	–
Battini et al. (2018)	VR, IMU	RULA, OCRA, OWAS
Bortolini et al. (2018)	DC	OWAS, REBA, RULA, IOSH, EAWS
Battini et al. (2018)	Heart rate monitor, VR, IMU	fatigue, RULA, OWAS, OCRA, hands position, hips movements
Caputo et al. (2019)	IMU	EAWS, OCRA, OWAS
Bortolini et al. (2020)	DC	OAWS, REBA, NIOSH, EAWS
Berti, Finco, and Battini (2021)	MOCAP	execution time
Bortolini et al. (2021)	DC	REBA and space analysis
Wilhelm et al. (2021)	DC	RULA
Simonetto, Arena, and Peron (2022)	IMU, VR	REBA
Borges et al. (2022)	IMU	RULA, NASA-TLX
Jara, Orejuela, and Baydal-Bertomeu (2022)	DC	RULA
Coruzzolo et al. (2022)	DC	RULA

Notes: DC: Depth Camera, VR: Virtual Reality, IMU: Inertial Measurement Units.

MOCAP can provide insights into worker productivity and suggest ways to optimise tasks and improve performance. Table 5 reports used technologies and measurements employed by main studies in assembly systems. We can notice that the main MOCAP technologies used in these studies are depth cameras and inertial measurement units (IMUs). More precisely, depth cameras used are Microsoft Kinect sensors, either V2 or, more recently, the Azure model. We can find a few works combining MOCAP and VR, which is interesting to simulate the assembly environment and make all possible tests in a virtual environment, making the operator safe while measuring his real computed ergonomics and productivity quantitatively. A piece of evidence from Table 5 is that the RULA metric is the most used in the literature as an automated tool. However, more adapted ergonomic measurements can be chosen depending on the case study and the nature of the assembly task. As explained in the previous section, RULA was developed originally for quasi-static manual evaluation. However, the ErgoSentinel tool allows real-time skeleton tracking and RULA processing (Manghisi et al. 2017). Finally, almost all works demonstrate their approaches to assembly case studies. Still, some of these studies include tasks with human-robot collaboration Ottogalli et al. (2021), which is a trend for the following assembly systems in Industry 5.0. Bortolini

et al. (2018) is the study that has carried out the most varied measurements on motion analysis to quantify human productivity issues automatically.

6. Human centred optimisation techniques

As mentioned earlier, ergonomics focuses on creating a working environment that maximises the employees' well-being and the organisation's effectiveness as a whole. This section examines the assembly line balancing with and without human-robot collaboration and job rotation scheduling optimisation models incorporating physical and ergonomic concerns. For each study, we briefly overview the modelling approach, the designed solution algorithms, and the ergonomic risk estimation functions. Table 6 shows a broad summary of the contributions.

6.1. Assembly line balancing

The purpose of the assembly line balancing (ALB) problem is to assign assembly tasks to stations in a way that maximises the given objective function. Jaturanonda, Nanthavanij, and Das (2013) create an assembly line balancing issue with two weighted objectives: balancing ergonomic risks among stations and balancing the distribution of station times. This research includes RULA risk estimates. The authors coupled an iterated local search method based on task swaps and shifts with the

priority rule heuristic. The assembly line balancing problem, which Sternatz (2014) developed, describes typical constraints in the production of automobiles, such as multiple workspaces per station, limitations on task-to-station assignment, sequence-dependent setup times, and ergonomic constraints prohibiting station loads with high ergonomic risks. A heuristic to address this issue is proposed to solve the problem. With the given cycle time, Barathwaj, Raja, and Gokulraj (2015) seek to balance the assembly line while minimising the objective function, which is calculated as the sum of three factors: the total number of stations, the average deviation of station idle periods, and the overall ergonomic risks. The authors use RULA and propose the Genetic Algorithm (GA) as a solution approach. Using numerous lexicographically organised objective functions, Akyol et al. (2016) take into account concurrent worker-to-station assignment and assembly line balancing. The first-tier goal is to reduce the cycle time for the specified number of stations. The ergonomic goals are additional goals (such as minimising average ergonomic risks, minimising the average deviation of ergonomic risks among stations, and minimising the number of stations with high risks). With OCRA, the authors assess ergonomic risk, and to address the posed issue, they provide a multi-start greedy heuristic method.

According to A. Otto et al. (2017), if task-specific parameters of the assigned tasks are included to quantify ergonomic risks at stations, the resulting assembly line

Table 6. Human-centred optimisation studies in assembly systems.

Type of problem	Study	Ergonomic risks in		Measurement	Resolution Approach	
		Constraint	Objective			
ALB	Jaturanonda, Nanthavanij, and Das (2013)	✓		RULA	Heuristic (LS)	
	Sternatz (2014)	✓		Force load	Heuristic	
	Barathwaj, Raja, and Gokulraj (2015)	✓		RULA	GA	
	Akyol et al. (2016)	✓		OCRA	Heuristic	
	Bautista, Alfaro-Pozo, and Batalla-García (2016)	✓		OCRA,RULA	GRASP	
	Battini et al. (2017)	✓		Energy expenditure	MIP	
	Tiacci and Mimmi (2018)	✓		OCRA	GA	
	Azizoğlu and Imat (2018)		✓	–	BB	
	Zhang et al. (2020)	✓		OCRA	IPG	
	Finco et al. (2020)	✓		Energy expenditure	heuristic	
	Finco, Abdous, et al. (2021)		✓	–	heuristic	
	Abdous et al. (2022)		✓	Quantitative fatigue	Exact solution	
	Freitas, Lima, and Gaspar (2022)		✓	–	AC method	
	JRS	Michalos, Makris, and Chryssolouris (2013)		✓	Fatigue, Repetitiveness	Heuristic
		A. Otto and Scholl (2013)		✓	EAWS	Heuristic (LS)
Mossa et al. (2016)		✓	✓	OCRA	MILP	
Yoon, Ko, and Jung (2016)			✓	REBA	–	
Moussavi, Mahdjoub, and Grunder (2016)		✓		Worker efficiency,	MILP	
Song et al. (2016)			✓	NIOSH-Eq, Force loads	Heuristic	
Moussavi, Mahdjoub, and Grunder (2018)		✓	✓	Daily workload,	multi-objective MILP	
Moussavi et al. (2019)		✓	✓	Cumulative workload,	MILP	
ALB-HRC	Dalle Mura and Dini (2019)		✓	Energy expenditure	GA	
	Weckenborg and Spengler (2019)	✓		Energy expenditure	MILP	
	Stecke and Mokhtarzadeh (2022)	✓		Energy expenditure	BD algorithm	
	Weckenborg, Thies, and Spengler (2022)	✓		Energy expenditure	Multi-objective MIP	

balancing problem falls under the category of the Time and Space Constrained Assembly Line Balancing (TSALB) Problem. With the specified number of stations and task-specific ergonomic factors, Bautista, Alfaro-Pozo, and Batalla-García (2016) built up a TSALB problem. They consider two issue versions with two different objectives: to reduce the absolute variances between ergonomic risks of stations and limit the maximum ergonomic risks for a station. The authors suggest measuring ergonomic risks using tools like OCRA, RULA, or NIOSH-Eq along several dimensions, then averaging those measurements solely when calculating the objective function. For a case study involving a power train facility in Spain, the authors created a multi-start metaheuristic greedy randomised adaptive search procedure (GRASP) and contrasted it with IBM ILOG Cplex.

Battini et al. (2017) suggested balancing the assembly line while making a judgement about feeding the pieces. Additional planning flexibility made possible by integrated planning may be implemented to reduce ergonomic risks at work. In a thorough case study on the assembly of a self-priming pump, the authors have formulated the integrated assembly line balance and components feeding planning problem, suggested a mixed-integer model, and compared integrated planning to a typical hierarchical planning approach. A method for designing asynchronous assembly lines that complies with ergonomic law is created in Tiacci and Mimmi (2018). The OCRA index is regarded as a tool for evaluating ergonomic risk. It is suggested to use a GA that can balance and sequence data as well as evaluate ergonomic dangers. The method allows for designing line configurations while considering various complex industrial case characteristics, including mixed model assembly lines, stochastic task times, task precedence restrictions, equipment, and line feeding duplication costs related to parallel workstations, and mixed model assembly lines. The proposed models are evaluated using data from a genuine industrial situation involving a business that sells agricultural equipment. By reducing the sum of the squared deviations of station loads from the cycle time, Azizoğlu and Imat (2018) investigated workload smoothing in ALB and suggested a branch and bound (BB) algorithm to address the issue. To simultaneously reduce cycle time and ergonomic risk of stations for a U-shaped AL, Zhang et al. (2020) designed a multi-objective restarted Iterated Pareto Greedy (IPG) method. They employed the OCRA index to determine the ergonomic risk of each station. They suggested two greedy and local search algorithms to enhance the exploration of the solution space and a heuristic technique to enhance initial solutions. The authors evaluated the

proposed solution approach against several cutting-edge meta-heuristic algorithms and found it superior.

Finco et al. (2020) created a heuristic algorithm to balance an assembly line that considered rest periods to offset ergonomic hazards and station-specific ergonomic risk indices. The rest allowance is calculated for each station based on how much energy is used by the duties assigned to each station. The data supported the effects of rest breaks on the assembly line's productivity. Later, a multi-objective assembly line design challenge was put out by Finco, Abdous, et al. (2021) to reduce equipment investment costs and exposure to vibration. In 2021, Finco, Calzavara, et al. (2021) tested a new methodological approach in a real case application. This approach included physical fatigue and rest allowance as ergonomic parameters in mixed-model assembly line problems. Cycle duration and worker fatigue were considered when Abdous et al. (2022) created a fatigue criterion and multi-objective model to solve the ALB problem. Freitas, Lima, and Gaspar (2022) have provided a task scheduling optimisation model utilising a methodology based on the Ant Colony (AC) optimisation approach to reduce the ergonomic risks seen in typical winery production processes. To do this, they evaluate the metabolic energy consumption during the execution of activities. The findings demonstrate that the tasks were reorganised by the degree of ergonomic risk while simultaneously minimising any potential ergonomic risks by rotating and alternating operative teams between those tasks with higher and lower values of metabolic energy required.

6.2. Assembly line balancing with human-robot collaboration

Cobots, or cooperative robots, have recently become popular in the ALB problem. The purpose of using cobots in manual assembly lines was to boost productivity (Dalle Mura and Dini 2019). This new issue was set up by permitting a worker and a cobot to occupy a common workstation to carry out activities at the same work-piece concurrently in a collaborative or parallel manner (Dalle Mura and Dini 2019; Weckenborg, Thies, and Spengler 2022). Additionally, repetitive jobs demanding workers' ergonomics should be eliminated. Making line-balancing decisions requires strict adherence to sequence-dependent start times between the two resources due to the possibility of collaborative tasks between human workers and cobots at shared workstations. This increases the complexity of the problem relative to the original ALB problem. Only four papers have been published thus far in this field of study, namely (Dalle Mura and Dini 2019; Stecke and

Mokhtarzadeh 2022; Weckenborg and Spengler 2019; Weckenborg, Thies, and Spengler 2022).

One of the first authors to address an ALB-HRC problem was Dalle Mura and Dini (2019). Using a GA, the authors optimised the number of workers, human ergonomic loads, and equipment, including cobots. They investigated the effectiveness of the GA using a real case study, assuming that one person and one robot could be assigned to each station. Later, a Mixed-Integer Linear Programming Model (MILP) model for the assembly line was created by Weckenborg and Spengler (2019), in which collaborating robots and human workers may be assigned to workstations based on ergonomics. By considering the cycle time, workstation, and resource costs per minute, the formulation sought to reduce the cost per cycle. The suggested methodology led to the realisation of cost-effective configurations. Recently, in addition to cycle time, the work provided in Stecke and Mokhtarzadeh (2022) also incorporates optimising the ergonomic risk, which is assessed using an energy expenditure approach. The Benders decomposition (BD) algorithm was developed to solve the problem being studied. The energy expenditure approach of the line cost is also included in Weckenborg, Thies, and Spengler (2022).

6.3. Job rotation scheduling

As previously mentioned, over the last decade, ergonomic factors have received increased attention in practice and scientific research, especially in the case of assembly systems where workers are exposed, over a long period, to different physical and mental workloads when performing repetitive tasks. Job Rotation Scheduling is a branch of operational research that analyses the workers' assignment to different tasks to balance the ergonomic risks of performing continuous risky tasks within a planning time (Destouet et al. 2023). Different ways to set up effective JRS that balance ergonomic risks among workers were examined in A. Otto and Scholl (2013). The authors confirmed that a comprehensive workload analysis is needed to define the objective functions of the mathematical model for JRS problems. In a recent survey on research considering the ergonomic factor in JRS, A. Otto and Battaïa (2017) provided an overview of existing optimisation approaches that consider physical ergonomic risks. According to the authors, JRS should ensure a balanced distribution of risks among individual work assignments when workers are spending their whole shift at workplaces with high demands. Accumulated fatigue could enhance human errors and, therefore, affect the product's final quality. Workers, products, and assembly environment characteristics impact the assembly task probability of error occurrence (Michalos, Makris, and

Chryssolouris 2013). Overall, existing studies examine several possible ergonomic objective functions, such as the minimisation of the average ergonomic risks. Mossa et al. (2016) described, for example, a job rotation-scheduling problem in which productivity rates depend on the workers' skills. The authors estimated ergonomic risks with OCRA and formulated two mixed-integer non-linear models to increase productivity as well as to reduce and balance ergonomic risks simultaneously by an appropriate rotation of workers. Song et al. (2016) formulated a job rotation scheduling problem considering risk factors, such as workload in manual material handling activities. The risk estimations depend on the workers' health state. The authors designed a heuristic algorithm and presented a case study where the computed job rotation schedules outperform the status quo job rotation schedule used in the company.

In JRS problems, planners can limit the risk analysis to some important production risk factors, such as noise. However, more general analyses of postures using measurement tools deserve to be explored. Yoon, Ko, and Jung (2016) proposed a mathematical model to reduce cumulative workloads on the same body part. They used the REBA tool to identify and assess the physical workloads. The authors ignored the learning aspect of their model.

Moussavi, Mahdjoub, and Grunder (2016) proposed a JRS model that can perform workforce scheduling in a real-time assembly line. They investigated the workers' ergonomic factors to affect the most appropriate worker for each task. In further research, Moussavi, Mahdjoub, and Grunder (2018) proposed a multi-objective JRS approach to balance the workload and optimise the production time simultaneously. In addition, they analysed different workstations to evaluate the physical workload of each job. Then, they proposed a MILP to schedule job rotation to optimise the cumulative workload. The objective of their model is to minimise the maximum daily physical workload to which the workers are exposed. Ergonomic restrictions are taken into account in the constraints of their model (Moussavi et al. 2019).

7. Discussion and future directions

The study of different works of the assembly system, with the operator, well-being, and productivity at the centre on different levels, leads to several observations and ways of improvement. Below, we mention those insights:

- The assembly process's frequent use of repetitive motions and handling large objects are two crucial factors that could put a worker under too much stress. Depending on the anthropometric and physiological

characteristics of the worker, a production line's relative workloads and assembly operation distribution can significantly improve ergonomics.

- Despite exploring real-world scenarios in numerous studies, further research is required to incorporate real-time statistical data and real-world measurements to identify the factors that impact human safety. As highlighted in the state-of-the-art study by Katiraei et al. (2021), these factors can be measured and validated in future human-centred models utilising various recent technologies. Suitable technologies should be capable of tracking employees, providing performance feedback, and swiftly assessing their individual traits and behaviours, thereby aiding in achieving this goal. Real-world data also plays a crucial role in accurately validating mathematical models and procedures.
- Further research may enhance the strategy shown, defining the optimum AI system and the best sensor placement, as well as proposing the development of additional ergonomic analysis techniques distinct from those already employed and accepted by classical ergonomics. Actually, only traditional visual ergonomic assessments are employed to assess human safety in most prior assembly systems studies. More advanced ergonomics metrics like HARM, SWEA, NERPA, ALLA, PERA, WERA, and SES can be considered and combined to optimise human factors better.
- To execute targeted workplace adjustments that ensure the anticipated productivity and safety levels, ideal work conditions can be tailored to certain worker categories, such as the elderly. This is done by taking into account some characteristics observable through sensors.
- Designers and engineers can adjust the assembly line workstation in a virtual environment before building it in the real world, which can save time and money by combining digital twins with VR. Additionally, a virtual version of the assembly line can be built and used to replicate the assembly process in various situations. This can be used to locate and remove bottlenecks, speed up assembly, and increase efficiency in general. Before it is built, personnel can receive training on using the assembly line workstation safely and effectively. Additionally, we may test various assembly line workstation arrangements, assess the ergonomics of the workstation for operators, and propose modifications to enhance comfort and output.
- When using depth cameras as part of a MOCAP system, the recorded information can also be used to produce a fused point cloud that can be used for motion

tracking, object segmentation, and recognition, such as following tools or components around a workspace.

Another line of research could be based on current legislation and occupational medicine surveys to help better define the factors characterising a given work's arduous aspect. For example, the SUMER survey is a study conducted by the French Ministry of Labour to assess the physical and mental demands of jobs in France (Niedhammer et al. 2020). The survey uses the 'hardship index' to quantify the difficulty and stress associated with different types of work. This index considers several factors that can be grouped into six 'physical working conditions' (Havet and Penot 2021): marked physical constraints, atypical work rhythms, and aggressive physical environment. Automation of the quantification of the hardship index could be developed. It can be done according to the following actions: (i) map all the workstations of the system studied (e.g. an assembly workstation), (ii) associate for each workstation a set of tasks necessary to perform a predefined work (e.g. the assembly of a product), (iii) decompose each task into a set of actions, movements or gestures to understand how it is accomplished and identify occupational exposures that may have detrimental effects on health. Therefore, the hardship index could be integrated into business decision support tools to have a flexible distribution of work and thus increase productivity.

Regarding human-centred technologies, all the mentioned industrial systems providing a real-time stream of 3D data can generate local or distant avatars, including a digital twin to be used remotely for demonstration training or education. These 3D data can also feed ergonomic methods computing to provide rapid MSD scores. Moreover, it is also possible to use MOCAP technologies to measure the synchronisation between people or even with a digital twin. This synchronisation of humans has been demonstrated for musical rhythm by Bayd et al. (2022). Non-verbal communication between humans can also be monitored with the same technologies. With 6DoF trackers placed on the cobots, interactions, collaborations and safety rules with human co-workers equipped with MOCAP devices will also be determined and controlled in real-time in manufacturing. Shortly, the digital twin in Augmented Reality will be accessible as a ghost guide in optimised manufacturing, where the virtual workshop will also be digital.

Considering the above observation and open possibilities, we propose a new human-centred optimisation framework as shown in Figure 8. It consists of an iterative process which explores the interdependence

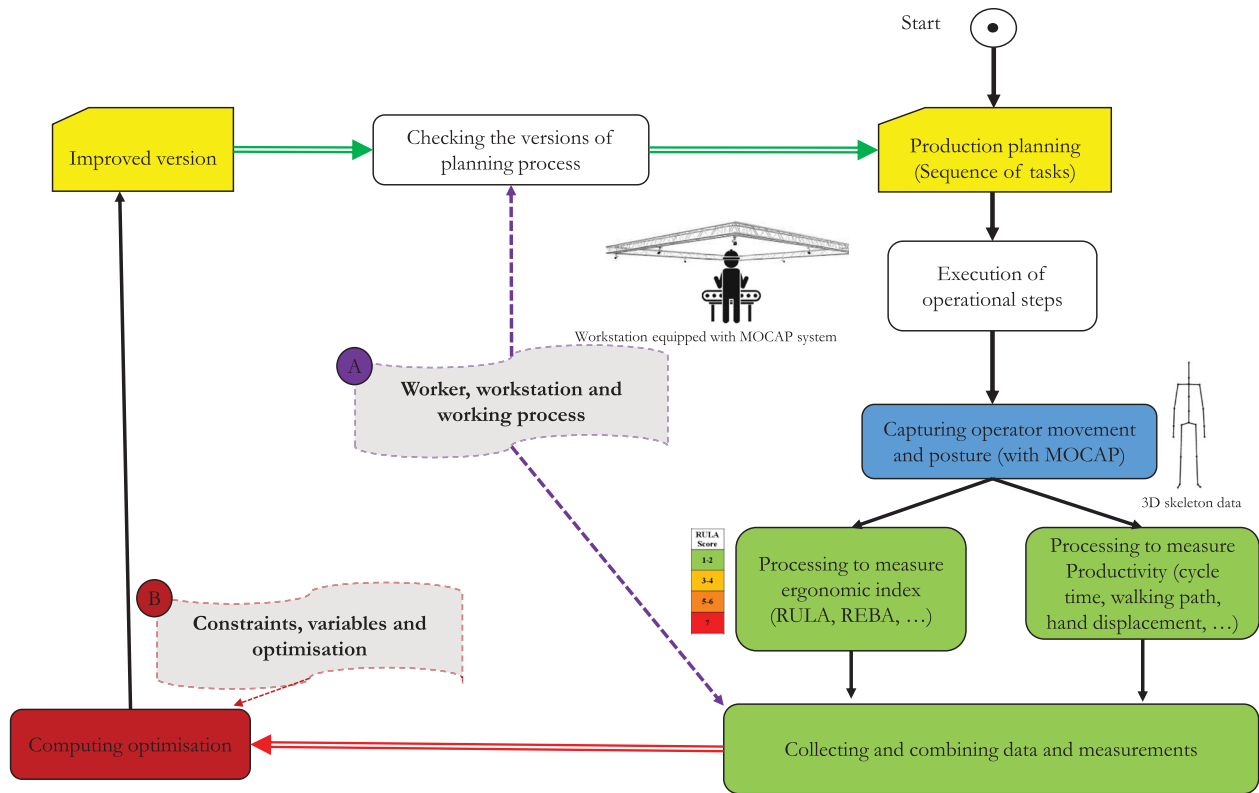


Figure 8. Flowchart of the proposed human-centred optimisation framework in an assembly system.

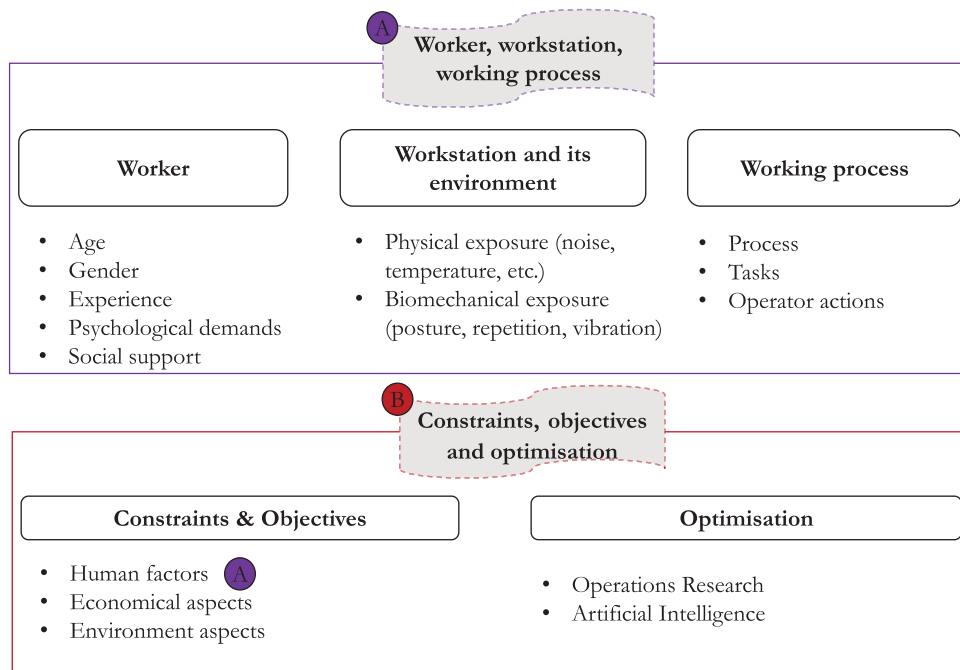


Figure 9. Details on Human factor and optimisation information required for the proposed framework.

between human factors and productivity. Starting from production planning, for a given real case study, the main steps of this framework are as follows:

- The operator executes the tasks in his environment equipped with MOCAP technologies carefully positioned;

- In parallel, MOCAP will capture informative data on human posture movements and gestures;
- This data will be processed to deduce ergonomic and productivity measurements;
- The measurements and information about each worker, workstation, and working process (see Figure 9(a)) are collected and combined to deduce quantitative indexes such as hardship index;
- For this step, constraints, objectives, and optimisation models should be defined and fixed depending on the industrial needs, expected productivity and well-being of the workers (see Figure 9(b)). This information, coupled with computed indexes, will be integrated into the existing decision-making tools that improve the production plan while ensuring flexible and equitable distribution of work among workers.
- Before putting this new plan into action, a checking phase must be done to revise the current information offered in Figure 9(a).

After this final checking phase, a new production plan is available, considering all assembly system layers (see Figure 1) and various human factor constraints. We can choose to maintain this solution or reevaluate it by looking for a different/better one that meets the objectives under a variable and uncertain environment.

8. Conclusion

In this paper, we presented a literature review of the most studied works with different MOCAP technologies, e.g. optical, inertial and miscellaneous, that help to register the static postures and the dynamic movements of an operator during the assembly process. The measurements resulting from the information provided by the MOCAP technologies about the evolution of the position and orientation of the operator body are identified in different related studies. Mainly, works that consider automatic evaluation of ergonomic indices and productivity indication are reported. Also, we have looked at the job rotation scheduling and assembly line balancing optimisation models that incorporate physical ergonomic concerns. Each study includes a summary of the ergonomic risk measurement techniques used. We note whether the models incorporate ergonomics as constraints or objective functions, and we detail the strategies for designing optimisation solutions.

Our paper went through all the layers necessary for implementing a work plan, from the acquisition system necessary to measure the ergonomics and the operator's productivity to the injection of these measurements in the optimisation models.

Finally, we proposed a human-centred optimisation framework for assembly systems. This latter is an iterative process where real measurements of the human resources are integrated as constraints and/or objectives to the optimisation processes. Thanks to this framework, an industrial production plan can be defined and updated according to (i) the production needs, (ii) the characteristics of workers, and (iii) workstations and the related environment.

Notes

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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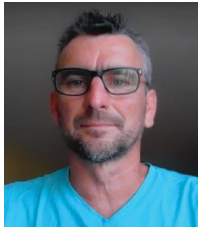


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