DESIGNING HYBRID HUMAN-MACHINE WORKPLACES

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During the transition to Industry 4.0, workplaces are being transformed from manual through human-machine hybrids to automated, autonomous and smart ones. Each of the aforementioned designs represents a development challenge. A particular challenge is the development of hybrid workplaces, where using the potential of man and machine to the maximum extent possible is necessary. Lean principles are followed in designing workplaces and processes, reflected in the efficient use of time and minimized losses, as well as ergonomics principles. Due to the lack of labor force and the aging of the population, concern for maintaining employees' health is an important guideline for designing workplaces for the future. Knowing the basics of lean, time management and ergonomics while simultaneously learning about the computer environment for designing workplaces can be a good starting point for the prudent designing of the renovation of traditional workplaces into Industry 4.0 workplaces.

Keywords:
hybrid workplace,
EAWS,
MTM,
EmaWD,
simulation

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1 Introduction

The introduction of digital technologies and automation in industrial environments–including collaborative robots (cobots), algorithms, artificial intelligence, the Internet of Things (IoT), big data, and cyber-physical systems (CPS) –is ushering in a new paradigm known as the Fourth Industrial Revolution (Cunha et al., 2022). This revolution is also referred to as Industry 4.0 (I4.0), Factories of the Future (FoF), or even Smart Manufacturing (Iordache, 2017; Gualtieri et al., 2020; Kadir & Broberg, 2021). Within this movement, interconnected or networked smart factories are envisioned, enabling efficient data collection and processing, automated management and operation coordination, and real-time operational monitoring (Moro et al., 2019; Çinar et al., 2021). Following this trend is expected to give companies a competitive advantage. But what does it mean to follow the trend? It involves transforming companies from novices to mature Industry 4.0 players. Part of this transformation includes reshaping traditional jobs that involve "repetitive tasks." Such jobs top the list for automation (e.g., Frey & Osborne, 2017) and productivity improvements through human-machine collaboration (Stern & Becker, 2019; Broday, 2020).

Equipped with new technologies, operators working on production floors will perform their tasks in cooperation with numerous technical innovations. In this context, the human operator–referred to in the literature as the "Operator 4.0"–is typically characterized by the technologies they use. For example, when using exoskeletons, the worker is portrayed as a super-strong operator or a healthy worker, as they utilize smart wearable solutions that collect psychophysiological data (Romero et al., 2016a; Ruppert et al., 2018). Some authors emphasize that new technologies, particularly exoskeletons and cobots, have the potential to improve productivity and workplace health (e.g., by preventing musculoskeletal disorders through reduced strain on the musculoskeletal system) (Cimini et al., 2020; Ranavolo et al., 2021). However, the mere use of technology does not guarantee reduced risk of musculoskeletal problems, as noted by Cockburn (2021) and Bounouar et al. (2022). There is also a belief that relieving workers from repetitive and monotonous tasks through technology could help enhance their skills–especially regarding system supervision. In this sense, it is expected that workers will become more skilled and autonomous as a result of technological integration (Romero et al., 2016a; Thun et al., 2019; Broday, 2020). Nevertheless, concerns remain that the adoption of new technologies may lead to increased employee surveillance (e.g., through sensor-based applications), intensified work, gender segregation, and reduced worker decision-making (Piasna & Drahokoupil, 2017; Moro et al., 2019; Beer & Mulder, 2020; Kaasinen et al., 2020; Kadir & Broberg, 2020; Golsch & Seegers, 2021).

The extent of the impact of technology-driven changes on workers' health and work is still largely unknown (Badri et al., 2018; EU-OSHA, 2018; Bobillier Chaumon, 2021; Zorzenon et al., 2022). Health challenges potentially arising from I4.0 include:

– Mental health concerns stemming from reduced autonomy and rising skill demands,
– Increased cognitive workload due to the use of automation technologies such as cobots and automated vehicles,
– Job insecurity linked to increased dependence on technology (Golsch & Seegers, 2021; Kadir & Broberg, 2021; Reiman et al., 2021).

Aligned with the concept of I4.0 as a "new industrial stage," research still predominantly focuses on the technical aspects of I4.0 transformations, rather than on human labor (Neumann et al., 2021; Barcellini et al., 2021; Bentley et al., 2021). The neglected social dimension of the I4.0 workplace includes working conditions, new work organization models, methods of worker-technology interaction, new constraints and resources introduced by technology, changing skill requirements, learning opportunities, or emerging risks that may threaten workers' health and well-being (Barcellini, 2019; Bounouar et al., 2022). According to Moniz & Krings (2016), these issues are often addressed only from the perspective of technical improvements and safety in relation to worker-technology interaction. Continued neglect of the social dimension of the I4.0 workplace in both theory and practice calls into question the success of I4.0 approaches and their impact on the people required to sustain them (Neumann et al., 2021).

In planning I4.0 implementations, it is necessary not only to focus on technology but also on the operators and their work activities. In addition to ensuring time-efficient operations, it is crucial to assess the risks to which Operator 4.0 will be exposed and the health impacts of their work.

2 The Concept of Operator 4.0 and the Status of Human Labor in Industry 4.0

The analysis of industrial transformation primarily anticipates the development of automation and self-management components, but it still relies on human presence. Instead of replacing humans with technology, the focus of Industry 4.0, according to many researchers (e.g., Cimini et al., 2020; Paliga & Pollak, 2021), is on relieving workers from strenuous and monotonous tasks and developing new skills that enable them to manage advanced and complex systems. The role of the worker, referred to as Operator 4.0, involves taking on newly configured activities within the work system. Currently, there are two visions for achieving this. The first envisions the human operator as empowered by technology and transformed into a "smart operator" through the use of smart technologies (Romero et al., 2016a). The second suggests that the operator may not be capable of handling all the demands posed by new technologies and will require training and reskilling to adapt to these changes (Li, 2022).

While literature continues to assume that humans will play a central role in managing Industry 4.0 systems, the definition of the operator remains blurred and is conceptually unified under one vision, described by Romero et al. (2016a, 2016b). According to Romero et al. (2016a), operators in Industry 4.0 are defined by the technological resources they use. They are classified into seven main typologies, which do not reflect different worker types, since multiple technologies can be used for the same job:

- Super-strength operator (using exoskeletons),
- Augmented operator (using augmented reality),
- Virtual operator (using virtual reality),
- Healthy operator (using smart wearables to measure physical activity),
- Smart operator (leveraging available smart technologies),
- Collaborative operator (working with cobots),
- Analytical operator (using and analyzing big data collected by the system).

According to this vision, smart factories are expected to harness not only the benefits and capabilities of smart machines through human-machine interaction, but also to empower their operators with new skills and tools (Romero et al., 2016a; Patriarca et al., 2021; Shi et al., 2021). These operators are expected to (1) have control over work processes and associated technologies, and (2) possess autonomy in developing their own skills. Therefore, Operator 4.0 is typically portrayed as an intelligent and skilled operator who uses technology according to their needs (Romero et al., 2016b; Kaasinen et al., 2020), or, in other words, an "industrial worker whose cognitive, sensory, physical, and interactive abilities are enhanced through interaction with Industry 4.0 technologies" (Gazzaneo et al., 2020, p. 221).

Gajšková et al. (2020) observe that I4.0 technology enables Operator 4.0 to decide independently–based on work circumstances–whether, how, and when to use the technology. For this reason, I4.0 is expected to transform work from repetitive, low-skilled, and physical labor into work that involves more complex and cognitive tasks, as decentralized decision-making grants workers greater autonomy. It should also be recognized that the more cognitive capabilities a task requires, the harder it is to claim that such tasks can be replaced by technology (Blštáková et al., 2020; Cimini et al., 2020; Golsch & Seegers, 2021). As work requirements become more complex, these systems may demand greater specialization, flexibility, and adaptability, increasing the need for qualifications and technical skills (Blštáková et al., 2020; Ivaldi et al., 2021). Mark et al. (2019) add that assistance systems can provide better opportunities for integrating and supporting workers with disabilities. Including these workers can enhance this potential and make the industrial sector a best-practice model within truly participatory and inclusive business environments.

These qualifications and technical skills are encouraged by work situations in specific contexts and develop through practice (Teiger & Lacomblez, 2013), rather than being acquired before such situations arise. Training can contribute to their development, but no universal learning or workplace training system exists. Research on digital learning environments is still emerging and mainly limited to demo applications (EU-OSHA, 2018; Engeström, 1999). On one hand, technology can create opportunities for new forms of on-the-job training, such as digital work instructions or virtual training (Hoedt et al., 2020; Chistyakova et al., 2021). On the other hand, training is more effective when it integrates real work situations and everyday use of technology (e.g., Galey et al., 2020).

The concept of Operator 4.0 remains vague, as does the status of human labor in the conceptualization of Industry 4.0 work scenarios, which continue to be overshadowed by assumptions of fully capable, healthy, young, gender-neutral, and highly skilled workers. In practice, however, many risks and negative effects of Industry 4.0 for workers are already emerging. Some of these are discussed in the following chapters (Cunha et al., 2022).

2.1 Risks and Impacts of Industry 4.0 on Health

The relationship between humans and technology is established within a specific context, influenced by a particular form of work organization. This means that technology is neither universal nor transferable from one environment to another without consequences for the activity carried out within that environment. Therefore, rather than merely identifying risks caused by technology, it is more important to understand them within the specific contexts in which they occur (Adriaensen et al., 2019).

Although automation has led to a reduction in manual labor, this does not mean that physical risks have been entirely eliminated from the workplace. Automated devices can also pose mechanical and electrical hazards, including noise, vibrations, and exposure to chemicals or radiation (Leso et al., 2018; Hoyer et al., 2020; Costantino et al., 2021). Additionally, less tangible risks–particularly psychosocial ones–often remain invisible (Badri et al., 2018; Bobillier Chaumon et al., 2019; Costantino et al., 2021). These include irregular work schedules (e.g., 12-hour shifts) due to continuous, automation-driven shift operations (Cunha et al., 2020), increased pressure to work at the pace of cobots, and heightened work surveillance through monitoring and tracking systems. Such working conditions negatively affect both physical and mental health and may manifest as musculoskeletal disorders, technostress, or anxiety (Valenduc & Vendramin, 2016; EU-OSHA, 2018; Ghislieri et al., 2018). These impacts can also present as physical pain or psychological distress. Health deterioration can be prevented by monitoring and addressing risk factors. The rise of robotics may increase isolated work and reduce contact between colleagues, contributing to workers' perceptions of losing control over their professional practices and the shared standards for quality and healthy work (Bobillier Chaumon et al., 2019).

While new technologies can enhance the value of work, they may also constrain workers' activities through (1) increased prescription of tasks and (2) reduced operational autonomy. In this way, workers are not allowed to apply their professional knowledge and experience to achieve well-executed work, which is key to workers' identity and a foundation of mental health and well-being at work (Bobillier Chaumon et al., 2019). As Thun et al. (2019) note, the advancement of automation could jeopardize workers' autonomy.

Many Industry 4.0 studies have focused solely on the technical aspects of design, often ignoring or only partially considering the social relations they support (Sony & Naik, 2020). Since even physical issues such as musculoskeletal disorders are linked to organizational and psychosocial factors, their prevention cannot be analyzed independently of the context and the relationships within it (Coutarel et al., 2022). As a result, overlooking these contextual features can perpetuate negative effects for workers (Barcellini, 2019). In a qualitative study by Kadir and Broberg (2020), based on interviews with 15 workers and 20 decision-makers from 10 companies that recently introduced digital technologies, several factors were revealed that influence well-being and performance. These included knowledge of how new systems operate, employer support, job security, and both physical and cognitive workloads associated with using the technology. Furthermore, workers expressed concern about "causing errors or damaging expensive digital systems," particularly when they were not properly trained in their use.

Research in occupational psychology and activity ergonomics consistently highlights the essential role of participatory approaches in addressing such risks (Béguin & Cerf, 2004; Barcellini et al., 2015; Bobillier Chaumon, 2021). Nevertheless, many studies still focus on the potential of technology. For example, in the study by Gualtieri et al. (2020), a manual assembly station was redesigned as a collaborative one (with cobots) based solely on a physical ergonomic assessment and productivity gains.

Including workers' perspectives in design processes provides insights available only to those performing the work, as their views are grounded in real-world knowledge of daily operations (Rangraz & Pareto, 2021). In connection with innovation models that promote sustainable leadership and communication at work (Iqbal et al., 2021), involving workers in the design process fosters trust between workplace actors. This approach also allows workers to see how their work is valued and how it contributes to organizational success (Saabye et al., 2020; Rangraz & Pareto, 2021).

Despite the foundational goal of Industry 4.0 to use technical innovation to place humans at the center again (see Saraceno, 2020), human and technical aspects have been unequally perceived–on the assumption that operator adaptation to technology is essential for the reliable functioning of work systems. Nonetheless, the importance of the human operator in Industry 4.0 contexts now appears to be recognized in the literature (e.g., Fantini et al., 2020; Pacaux-Lemoine et al., 2022). Human involvement remains essential in environments characterized by heterogeneous technologies (e.g., cobots, exoskeletons, cyber-physical systems) (Barcellini et al., 2021). Beyond ensuring safe and effective interfacing between multiple technologies, the operator contributes to system reliability–for instance, by reconfiguring processes during unexpected events, managing task variability, and anticipating potential consequences of irregularities.

Current definitions of Operator 4.0 do not clarify whether the concept is gender-neutral and, if so, how changes in work and organization affect existing (or create new) gender inequalities, or how gender segmentation is intertwined with technological development in the Industry 4.0 era. Cunha et al. (2022) found that gender segregation persisted even after automation was introduced, acknowledging that such segregation is not independent from the historical knowledge of manual labor acquired by different generations of workers. In short, technology interacts with gender and has yet to be independent from it.

The aging workforce, expected to continue growing, poses a threat to the long-term sustainability of new Industry 4.0 work systems (Brozzi et al., 2020). With a large number of older workers likely to remain active longer, the need for safer work, accessible lifelong learning, and inclusive employment becomes increasingly clear (Gaudart, 2016). Some authors argue that Industry 4.0 offers advantages in this regard, as its systems automate physically demanding, repetitive, and monotonous tasks (Brozzi et al., 2020; Agnusdei et al., 2021). However, the learning demands of I4.0 systems are likely to favor new (possibly younger) workers who are "better equipped to learn" (Badri et al., 2018, p. 407). Moreover, simply introducing new technologies does not ensure that workers' needs for job stability and security will be met (Longo et al., 2020). On the contrary, increasing work intensity, the constant need to adapt to specific production demands–"which do not follow the same rhythms, demands, or goals" (Gaudart, 2016, p. 16)—and irregular work schedules (e.g., Cunha et al., 2020; Rangraz & Pareto, 2021), may undermine the sustainability of these new work systems.

2.2 Research Opportunities

Case studies involving workers as key participants, followed by an analysis of the health and well-being impacts of Industry 4.0-related work reorganization, are a necessary step for future research. This is particularly important as experience with these technologies still needs to be developed to better understand emerging risks related to work-related illnesses. In line with the Sustainable Development Goals (United Nations, 2020) and the findings that the Operator 4.0 is not a gender-neutral worker–and that work affects women and men differently (e.g., Messing & Silverstein, 2009) –gender dimensions must also be integrated into future research investigating such impacts, in order to promote healthier (Goal 3), more equitable (Goal 5), and more sustainable jobs (Goal 8). The key question, then, is: How can Industry 4.0 technologies serve as a driver for achieving these goals? (Cunha et al., 2022)

3 Simulation of Human Labor, 3D Production Planning, and Virtual Ergonomics with ema Work Designer Software

According to Spitzhirn et al. (2022), planning and designing production and work systems requires a holistic approach that considers both levels of planning–factory-level and workstation-level. Currently, separate digital tools are predominantly used for factory layout planning and detailed workplace system planning. This often results in workers being inadequately or insufficiently considered during the production planning process. Consequently, costly and time-consuming redesigns may be required to resolve problems in existing production and work processes.

Using the case of a washing machine assembly, an iterative approach is presented for digitally supported combined planning at both the factory and workplace levels. The overall design of the assembly line can be carried out using the ema Software Suite, which includes ema Plant Designer (emaPD) and ema Work Designer (emaWD). In the case study, emaPD is used to optimize production elements such as operational resources, layout, and logistics, considering material flow, lead times, and production costs. A simulation environment is used for detailed workstation-level planning with emaWD, which applies an algorithmic approach to autonomously generate human movements based on objective task descriptions.

The generated simulations are reviewed and optimized using production time evaluation (MTM-UAS) and ergonomic risk assessments (EAWS, NIOSH, reach-and-vision), as well as worker capabilities (e.g., age, anthropometry). This enables the design of an efficient factory with optimized material flow, minimized production costs and lead times, while considering spatial constraints and ergonomic factors. Ergonomically unfavorable tasks can be taken over by robots in hybrid workstations, thereby improving workplace ergonomics. This digital planning approach combining factory design (emaPD) and workstation planning (emaWD) enables early, coordinated, and efficient design of both cost-effective and ergonomically sound production systems.

3.1 Challenges in Designing Cost-Efficient and Ergonomically Suitable Factory and Work Systems

According to Spitzhirn et al. (2022), increasing cost pressure from competition, labor and material costs, greater product diversity, shorter product lifecycles, and rapid time-to-market cycles demand that production and work systems be planned and restructured more quickly and frequently (Spath et al., 2017; Bracht et al., 2018). In planning and designing production and work systems, factors such as cost, time, quality, time-to-market, and flexibility must be considered–alongside ergonomic workplace design and the allocation of labor based on skillsets (Schenk et al., 2014; Schlick et al., 2018).

Factory or production planning and work system planning typically involve different departments. At the factory planning level, focus is placed on production programs, space allocation, and the design of the factory and production systems. Work system planning involves workstation and process design–such as equipment layout and human-machine/robot interaction–according to economic and ergonomic criteria. While early, coordinated, and efficient factory, production, and workstation planning is crucial, it is often not carried out with sufficient accuracy (Bracht et al., 2018).

Many companies use digital tools for factory and workstation simulation and planning (Wiendahl et al., 2015; Bracht et al., 2018; Burggräf et al., 2021). Available software increasingly includes features like Integrated Factory Modeling (IFM), which offers more detailed insights than simple 3D visualization (Burggräf et al., 2021). However, separate tools are still often used for factory/logistics planning and detailed workstation planning (Bracht et al., 2018). These tools differ in terms of functionality and usability, they do not share a common database. As a result, data conversion into compatible formats is required, which is time-consuming and may lead to data errors or loss.

Using two or more software tools requires significant investment from companies and skilled experts who can operate multiple systems. Training these experts is costly and time-consuming. Moreover, not all tools offer interfaces for integration with other software, which leads to separate planning processes for the factory and the workplace. This can result in costly and time-consuming redesigns when solutions optimal in one tool prove suboptimal in the other. For the design and planning of factories and work systems, it is therefore reasonable and efficient to use a single software platform and a holistic approach that integrates both factory-level and workstation-level planning. This reduces planning costs, improves outcome quality, and minimizes the planning effort.

The following sections present an iterative approach to continuous digital planning between factory and workstation levels using the EMA software tool suite.

3.2 Digital Factory and Work Planning for Cost-Effective and Ergonomically Designed Production

Using the case of a production and assembly planning project for a washing machine, this section describes an iterative, combined approach to factory and workplace planning using the EMA Software Suite (Spitzhirn et al., 2022). The goals are to redesign the assembly line and optimize the production line. It is also necessary to evaluate whether the planned production program can be realized with the existing machinery and assembly capacity, and how to improve the overall economic efficiency of production while ensuring favorable ergonomic conditions for workers at individual workstations.

Based on the production program and product assortment, target quantities, planning period, and both quality and quantity requirements must be defined. The product itself must also be examined, as its components determine manufacturing processes, handling technologies, etc., while the product structure dictates the assembly sequence. Product modifications, such as simplifying or merging functional units, can affect technical, economic, and ergonomic conditions (e.g., weight, force, grip type) of production (Schenk et al., 2014; Bracht et al., 2018).

The washing machine consists of 86 components, including the frame, drum, drain pump, various hoses, pipes, and screws. These parts vary in shape, dimensions, and weight. The total weight of the washing machine is 82.95 kg, with component weights ranging from a few grams to over 10 kg. The product is manufactured in three color variations: white, blue, and orange.

The functionalities of the EMA software are illustrated through EMA Plant Designer (emaPD) and EMA Work Designer (emaWD). Both systems can be used independently or integrated into a single interface. Factory-level production and assembly planning is conducted using emaPD (macro-level), while detailed 3D visualization and workstation-level planning—addressing economic, temporal, and ergonomic criteria–is handled in emaWD (micro-level). Planning data can be exchanged directly and synchronously exchanged via a bidirectional interface between emaPD and emaWD.

Computer-aided modeling, analysis, and optimization of production is conducted in emaPD using mathematical and analytical methods (e.g., queuing theory per Manitz, 2008), factoring in lead times, spatial requirements, and production costs. Required input data include product details (planned quantities, bill of materials, batch sizes), process data (technological steps, packaging data), and resource data (availability, costs, area, number of shifts).

The first step is to assess whether the production goal (80,000 washing machines annually) is achievable under current conditions (e.g., number and types of machines). Bottlenecks, spatial requirements, or critical production paths can be identified to determine improvement actions (e.g., adding machines, buffer zones, shifts).

Further decisions must address in-house vs. outsourced production, machine types and equipment, and the macro-level work processes. emaPD can be used to create alternative machine setups and technological processes, simulating production scenarios while considering cost, resource availability, space, and production time. To analyze potential issues related to space, ergonomics, and timing for workers, emaPD results can be exported into emaWD. Interaction between a human operator–represented by a digital human model with customizable traits–and the workstation can be evaluated in emaWD. If results are unfavorable, workstations or tasks can be adjusted for ergonomic and economic improvements.

The Overall Equipment Effectiveness (OEE) can be calculated in emaPD to evaluate productivity and machine-related losses. Material and manufacturing costs can also be computed in emaPD, including storage, machine (hourly or fixed/variable), and purchased parts costs. When used alongside emaWD, investment costs for equipment can also be considered, influencing overall production costs. Production and assembly times in emaWD can be measured or estimated using the MTM-UAS standard time method.

emaPD evaluates total production capacity across all machines and factory space, not just individual workstations. Different workstation layouts and process variants can be simulated and assessed using Key Performance Indicators (KPIs) such as space requirements, production volume, and cost. Detailed workstation layouts and equipment placement within them can be designed in emaWD and exported to emaPD, enabling material flow optimization based on transport intensity and effort. The planning process can also integrate physical workload data. Standard machines and workstations created in emaPD can be imported into emaWD for 3D modeling.

Detailed workstation planning and design are carried out in emaWD using anthropometric human models–from small women to tall men with different capabilities (including age-related flexibility and strength)–to design efficient, ergonomic, and capability-based workflows (Ullmann & Fritzsche, 2021). The human model configurator allows users to add models into the 3D environment.

Manual and semi-automated tasks and human-robot interactions can be simulated in emaWD. The path and motion of the digital human model are generated automatically based on parameterized activity descriptions (using the task library in the ema simulation environment) and definitions of basic working conditions (e.g., objects to be handled, target positions, etc.).

Users can apply a variety of established analysis methods, including standard time estimation using MTM-UAS (Bokranz & Landau, 2012), walking distance, value-added activity percentage, health risk assessment via EAWS (Ergonomic Assessment Worksheet) (Schaub et al., 2012), and the NIOSH lifting index (Waters et al., 1994). These analyses in emaWD help identify economic and ergonomic issues (Fritzsche et al., 2019b; Spitzhirn et al., 2022). Improvements can be implemented by adjusting the work environment (e.g., table height), transferring harmful tasks to robots, or redistributing tasks across workstations. The final scenario is documented in the EMA suite using reports, images, videos, and production process simulations.

3.3 Results of Iterative Digital Production Planning Using Digital Factory and Workplace Design

A total production volume of 80,000 washing machines is planned, distributed across three color variants (white: 55,000, blue: 15,000, orange: 10,000). Figure 3.1 illustrates example outputs obtained using the emaPD tool, specifically for the washing machine production scenario.

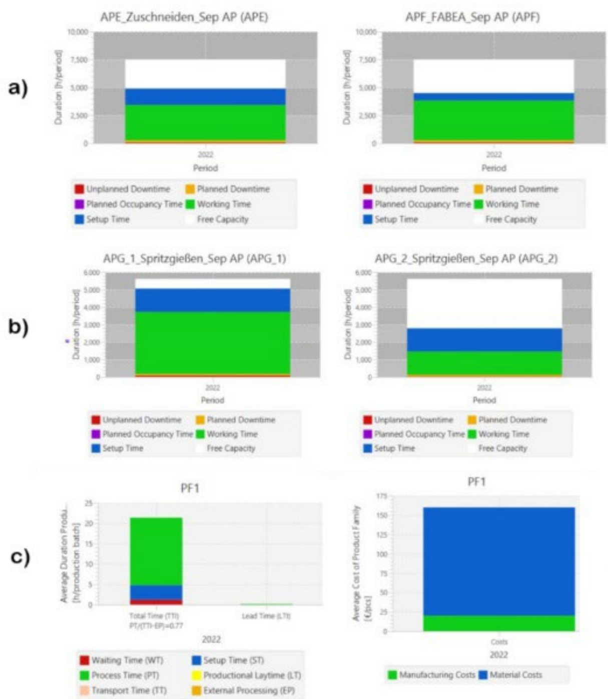

Figure 3.1: Examples of Results in emaPD for Washing Machine Production

Source: own source

Considering machine availability, delivery costs, lead times, and resource constraints, 23 components are produced in-house, while 63 are purchased. The simulation of the current production state showed that the system is unable to fulfill the entire order volume, with a shortfall of 7,587 units. By increasing the number of cutting machines from two to three, adjusting and synchronizing batch sizes, and optimizing execution times (e.g., reducing wait times, redirecting orders to less busy machines), the required production volume was achieved.

On the assembly line, which consists of eight connected workstations with a total of 14 employees, blocking times at station APB were reduced from 348 hours to 180 hours, and at station AP1 from 133 hours to 60 hours. Downtime at AP1 was also eliminated (reduced from 86 hours to 0 hours) by introducing five buffer zones between APB and AP1 and eight buffer zones between AP1 and AP2. The production area covers 530.06 m², generating production costs of €159.98. Utilization rates vary by workstation–from 98.6% on the assembly line to 48.6% on injection molding machine type A.

Following rough planning, the factory layout and assembly line were transferred from emaPD to emaWD. In emaWD, the material flow was refined, including path networks and layout simulations. Additional elements such as conveyors, shelves, and boxes were added, along with necessary input data (e.g., weights, masses, and exact layout coordinates) for ergonomic and time assessments.

Analysis of current assembly workstations using an average male digital human model showed 4 red, 7 yellow, and 3 green workstations according to the EAWS ergonomic assessment. Red and yellow ratings indicate increased risk for musculoskeletal disorders. An ergonomic assessment was also conducted based on worker age. For this purpose, the simulation model was supplemented with additional human models:

(1) a short, older woman (age group: 60; 154 cm; reduced age-related mobility),

(2) a tall young man (age group: 20; 194 cm; age-appropriate mobility and strength),

(3) a tall older man (age group: 60; 183.5 cm; reduced mobility and strength due to age).

The feasibility test showed that a medium-sized man, a tall young man, and a tall older man can perform all production activities. However, the shorter older woman was unable to reach all required locations on the washing machine assembly conveyor. A visual summary can be generated to show tasks that the shorter elderly woman cannot perform. For example, a woman around age 60 would likely be unable to push the drum into the washing machine frame (workstation 1R), which also affects station 1L, where both operators fasten the drum together.

Human differences in anthropometry, flexibility, and maximum strength also affect workload assessment and biomechanical risk scores per EAWS. Table 3.1 shows that physical workload per EAWS at workstations 1R, 2R, and 4L is higher for the short, older woman compared to the middle-aged man and the older man. Additionally, as shown on Table 3.1, task feasibility is limited or infeasible at stations 1R and 4L due to short stature and age-related mobility limitations (Spitzhirn, 2017).

Table 3.1. Summary of Ergonomic Test Results Based on Feasibility Testing and EAWS for Workstations 1R, 2R, and 4L

	Workplace 1R			Workplace 2R			Workplace 4L		
	M50-AK40	F05-AK60	M95-AK60	M50-AK40	F05-AK60	M95-AK60	M50-AK40	F05-AK60	M95-AK60
Feasibility	YES	NO	YES	YES	YES	YES	YES	NO	YES
= EAWS points [1]	61,5	(70,0) [2]	68,5	52,5	56,5	52,5	59	(63) [2]	37
+ points due to limb position	6	(5,5)	7,5	2	2	2	24	(28)	2
+ points due to forces	50	(59)	56	34	34	34	33	(33)	33
+ points for working with loads	-	(-)	-	16,5	20,5	16,5	-	(-)	-
+ extra points	5,5	(5,5)	5,5	-	-	-	2	(2)	2

[1] Legend: EAWS (high health risk > 50 points, potential health risk > 25 points, low health risk ≤ 25 points)
[2] not feasible based on feasibility check with emaWD
Source: Adapted from Spitzhirn et al., 2022

To improve ergonomic and economic outcomes, several corrections and enhancements were made to the simulation model. These measures were subsequently simulated in emaWD and evaluated using EAWS and MTM-UAS methods. The implemented improvements were as follows:

– A Fanuc CR35ia robot, capable of lifting up to 35 kg (washing machine drum = 30.7 kg), was introduced at workstation 1R (handling the drum), reducing the EAWS score from 61.5 to 23 points.
– A UR10e robot was added at workstation 2R (handling the rear panel), reducing the EAWS score from 52.5 to 32 points.

- A pedestal was introduced at workstation 4L (EAWS score reduced from 59 to 31.5) and at workstation 5L (EAWS score reduced from 40.5 to 40.0).
- The relay assembly task was moved from workstation 3L to 7R, improving ergonomics and balancing the line (EAWS score reduced from 55.5 to 42 points).

After reconfiguration, the cycle time was reduced from 70 to 60 seconds based on MTM-UAS, and workstations were time-balanced by reallocating tasks between them.

The optimized model data were transferred back from emaWD to emaPD. Due to workstation balancing and other improvements, the buffer capacity was significantly reduced—only the buffer between APB and AP1 was retained. Downtime on the conveyor was reduced to less than 50 hours, and production costs decreased by nearly 10%, while output increased.

4 Conclusion

The chapter *Designing Hybrid Human-Machine Workstations* defines the core concepts needed to understand a highly relevant topic in the era of digital transformation, Industry 4.0, and the push for sustainable operations. Employees are becoming Operators 4.0. Industry is not only facing a new technological revolution but also a fundamental change in working conditions, employee skill requirements, and qualifications.

As demonstrated, upgrading manual workstations to human-machine work environments must not focus solely on technology; it must also account for potential risks to employee well-being and health. This dual-focus facilitates smoother transitions to Industry 4.0, reduces resistance from workers, and results in more sustainable positive outcomes for both employees and companies.

The methods used to evaluate the economic and ergonomic value of workstations are not new—the novelty lies in how they are applied. Formerly done manually with pen and paper, today these assessments are performed using reliable digital tools. Results obtained with digital tools are fully comparable to traditional methods. One such tool, EMA Suite, was illustrated in Chapter 3, alongside methods such as EAWS, NIOSH, and MTM-UAS.

Comprehensive planning of hybrid human-machine workstations requires extensive knowledge of new technologies, logistics, process-based approaches, workplace ergonomics, time studies, lean methodology, sustainability, and digitization. We hope this contribution has demonstrated the need for a multi- and interdisciplinary approach to designing hybrid human-machine work environments. Rather than deterring practitioners, the scope of this challenge and the positive outcomes for workers and companies should encourage faster adoption of hybrid workstations in today's industrial settings.

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