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Abstract

Manufacturing processes and industrial systems gradually change their traditional layouts and configurations, preparing to introduce novel integrated human-robot technologies as collaborative robots and exoskeletons. Whether mass customization of lot size and the production mix discourages the adoption of capital-intensive automation, collaborative robots become affordable and effective and a hotspot of the debate on manufacturing systems. This paper provides a novel support-design framework for the cooperative robot system in labor-intensive manufacturing processes to aid layout and task scheduling design. Through an iterative closed-loop methodology, this framework explores the impact of a cooperative robot in a labour-intensive manufacturing system like the production facility of a food service company. The framework leads the designer through the re-layout of the end-of-line, the economic and technical feasibility analyses, using simulation to estimate payback and ergonomics benefits for workers. Within the proposed layout, we state that adopting a cooperative cobot for the end-of-line is affordable and ergonomically convenient without representing a safety threat for workers. The testbed confirms the framework as an enabling tool for human-robot technologies integration in current manufacturing systems under budget and workers-driven constraints.

Keywords: *Collaborative Robot*, *Technology integration, Industry 4.0, Ergonomics, Human-robot cooperation, Manufacturing systems.*

1. Introduction and background

The change of the production-demand patterns (Fetene Adane et al., 2019; Nunes et al., 2017), e.g., smaller lot size, order customization, along with the increasing attention paid to the worker's conditions (Haslam et al., 2005; Manu et al., 2012) boost the technological transition of manufacturing and assembling systems toward more human-care solutions and configurations built upon recognized synergies between the role of the automation and the operators (Sartal & Vázquez, 2017; Morgan et al., 2021). Whether mass customization of orders and production mix discourage the adoption of capital-intensive automation (Jaime & Eoin, 2020; Skare & Riberio Soriano, 2021), the use of collaborative robots is becoming competitive and widely discussed among scholars and practitioners (Lakshmi & Bahli, 2020).

Firstly, the hotspot of the debate is giving a straightforward but comprehensive definition of human-robot collaboration (HRC) solutions (Vicentini, 2020). L. Wang et al. (2019) provide an overview of symbiotic human-robot collaborative configurations with a taxonomy of relationships between the technology, the operator, and the manufacturing environment. They also summarize directions toward uncovered challenges like modeling workers' tasks through digital twins and simulation. Correia Simões et al. (2020) overview the factors influencing managers' intention to adopt collaborative robots in manufacturing companies with a survey involving enterprises and managers. Literature states that design approaches are focused on four main domains: control, technology, interface, and system integration (Gopinath & Johansen, 2016).

Four steps marked the evolution of manufacturing processes towards pursuing human-robot collaboration and system integration (Liu & Wang, 2017; Şahinel et al., 2021a; L. Wang et al., 2019a). One of the primary drivers of such evolution was moving the worker closer to automation technology and allowing contact between the human operators and the machinery.

In the first step of the transition, workers and automation technology are fully separated using physical barriers, as metal cages and protections. Such barriers define the limits of two different work areas with no possibility for exchanges or interactions. The aim is to prevent the workers' contact with the moving parts of machinery for safety purposes. Then, the coexistence of workers and machinery in the same work area is possible. However, non-physical separators (e.g., laser barriers) aim to stop the system if the workers access the machinery work area. The contact of workers and machinery during manufacturing processes is possible at the next step, in which the aim is cooperation during the work activity. Finally, contact is necessary where humans and collaborative robots collaborate and share the same work area.

So far, other drivers for the application of collaborative robots in manufacturing systems include reducing working costs (Dalle Mura & Dini, 2019), shrinking ergonomic impacts (Costa Mateus et al., 2019b), and aiding workers with deficits (Kildal et al., 2019; Mark et al., 2021). Despite such attempts, few compelling examples are still illustrated by the literature and industrial practice, demonstrating how meandering is the road toward such transition (Botti et al., 2015, 2017; Mark et al., 2021).

Table 1 summarizes attempts to re-design manufacturing/assembling processes regarding the applications of collaborative robots. It reveals those traditional targets of minimizing labor costs pair with enhancing the performance of workers and the manufacturing throughput, subjected to human safety regulations and constraints. Overviewing several laws and normative (ISO 12100: 2010; ISO 11161:2006; ISO 10218–1: 2011; ISO 15066:2016), Bi et al. (2021) underline the essential functional requirements of collaborative systems, like task's standardization and safety mechanisms. The standardization of the tasks and the management of safety entail interaction between man and robot (X. V. Wang et al., 2017) and strategies to exploit collaborative processes (Tlach et al., 2019).

Albeit collaboration provides benefits to workers, such a process represents a potential safety threat (e.g., injuries), regardless of the robot's size (Gopinath et al., 2018). Therefore, as collaborative tasks compel compliance with regulations, the manufacturing process's overall performance (i.e., throughput) might be reduced. To avoid such drawbacks, collaboration might be limited by organizing the process into sequential tasks, assigning alternatively to the robot and operator, or keeping the working environment separate, discouraging collaboration to warn by risks (Hippertt et al., 2019a). Because of the constraints above, truly collaborative tasks are limited to pick and place applications and simple assembling operations, as proved by Casalino et al. (2018) and Quenehen et al. (2019).

Table 1 summarizes the main factors to be investigated in manufacturing processes automation organized into columns. These are *Technology* (e.g., Robot or Cobot), *Objective*, *Target*, *Performance*, *Industrial Environment*, *Real Application* (i.e., real case-study), and *HR Relationships*. *Objective* stands for the target-designed technological aspects such as control or interface, whilst *Target* means the task performed by the Technology (e.g., Manipulation or Pick and Place). The *HR Relationship* describes the type of Human-Robot Interaction (HRI) (Baroroh et al., 2020; Oliff et al., 2020), which includes coexistence, interaction, cooperation, and collaboration between the technology and the operator (Vicentini, 2020; Villani et al., 2018; L. Wang et al., 2019c). Gao et al. (2020) underline the role of motion, computing, perception, and cognition to improve robotic applications. They present several intelligent robotic systems and enabling technologies like robotic networks, deeply learn robots, and human-robot friendly and natural interaction. Looking at Table 1, it is glaring that some performance indicators like improving throughput and safety are broadly treated together.

On the other hand, this table provides evidence of the lack of literature on cooperative robot systems' implementations for concurrent packing and load manipulation in a food production facility and other labor-intensive manufacturing environments. For instance, Arrais et al. (2021) developed a cooperative robotic system for industrial coating cells to avoid placing errors, increasing coating processes' flexibility and efficiency. Notwithstanding the implementation of safe HRC by tracking the worker's position inside the cell, no mention is given on regulations or ergonomics improvements.

Scholars and practitioners agree that the debate between automated and labor-intensive manufacturing is not solved by the advent of collaborative robots (Cohen et al., 2019). Indeed, labor continues providing added value to industrial operations through flexibility and adaptability (Antonelli & Stadnicka, 2019b) but requires considering workers' ergonomics (Weckenborg & Spengler, 2019), whilst automation increases the throughput. Ferreira et al. (2021) study the performance of some manufacturing lines by solving a task scheduling problem using robots and humans. They suggest that collaborative tasks improve the throughput, especially with many precedence constraints and low robot eligibility.

However, the case-driven environment of the application still plays a pivotal role in determining the success rather than the failure of HRC (Peralta & Soltero, 2020; Şahinel et al., 2021b), and several issues remain unhandled by current design frameworks.

The low capital cost of the technology advocates ever more exploring new industrial applications, case studies, and manufacturing processes, support-design frameworks able to incorporate safety and ergonomics as system design drivers (Bortolini et al., 2018; Maganha et al., 2018), and encouraging low-risk HRC are required (Bortolini et al., 2018; Maganha et al., 2018; Malik & Brem, 2021a). Lv et al. (2021) propose a new framework for HRC assembly based on digital twin. In order to investigate the optimal HRC strategy, they generate data from a digital human-robot motion twin and use an embedded optimization method to assess the resilience and efficiency of the overall manufacturing/assembly environment. Hence, the focus of ergonomics is the interactions among humans and other elements of a working system, including technology and machinery interfaces. The design of safe and sustainable systems includes ergonomics principles through the combination of a systematic and iterative process, an ergonomic design-driven approach, and a focus on optimizing both process performances and well-being (Wilson, 2014). Huang et al. (2021) present a new experimental robotic disassembly cell made of two collaborative robots and human workers. They use HRC to perform disassembly tasks in a shared workspace. Control design aims to employ collaborative robots to achieve complex disassembly tasks and safe HRI with a focus on the ergonomics of the processes.

The novel contribution of this work aims to present a systemic, multi-disciplinary and iterative approach encompassing human-robot cooperation aspects. To the purpose, we address the following research questions (RQs) in this paper:

- RQ1: Which are the most common drivers for robotizing labor-intensive manufacturing processes?
- RQ2: In a labor-intensive manufacturing process, how significant ergonomics benefits and cost reduction are and which drives the design most?
- RQ3: While introducing a collaborative robot, which task requires re-allocation or re-design?

This paper builds upon this statement and explores the underlined niche by designing and implementing a novel support-design framework for Cooperative Robot systems in labor-intensive manufacturing processes, shifting from technology-driven design to system-driven perspective. The framework lies on a closed-loop iterative methodology that integrates design tools and methods devoted to the different domains of the manufacturing system: layout, technology, interfaces, and control and interaction strategies. The design features and parameters are obtained after iterative refining and adjustment toward target performance. Concerning the literature, our framework considers ergonomics indicators and economic feasibility (i.e., payback period) of the HRC systems as key performance metrics.

The remainder of the paper is organized as follows. Section 2 introduces the methodology and describes the design tools incorporated in the framework. Section 3 illustrates a proof-of-concept as an industrial case study of the food catering industry. The discussion about the framework is proposed in Section 4, while Section 5 concludes the paper and lists hints for future research directions.

Author, year	Technology		Objective				Target				Performance					Industrial Environment				Real Application		HR Relationships			
	Cobot	Robot	CD	TD	ID	SAD	Ma	De	SM	P&P	T	C	WS	Sa	Erg	A	M	Pkg	FPF	P	I	Coe	Int	Coo	Col
Gopinath et al. (2016)	x		x		x	x	x			x	x			x		x	x			x			x		
Wang et al. (2017)	x					x	x								x	x			x	x				x	
Casalino et al. (2018)	x		x			x	x	x		x				x		x	x				x		x		
Gopinath et al. (2018)		x	x	x				x	x		x			x		x	x				x	x			
Hippertt et al. (2019)	x	x	x			x		x						x			x			x		x			
Kildal et al. (2019)	x		x		x	x		x						x		x				x					x
Mateus et al. (2019)	x*					x	x				x				x	x				x					x
Tlach et al. (2019)	x		x			x	x			x			x	x		x				x					x
Weckenborg et al. (2019)	x					x	x			x		x		x		x	x				x		x		
Quenehen et al. (2019)	x					x				x				x		x				x					x
Antonelli and Stadnicka (2019)	x		x				x			x				x		x				x					x
DalleMura and Dini (2019)	x			x		x	x			x		x	x	x		x				x					x
Gao et al. (2020)	x			x		x	x				x	x					x			x					x
Arrais et al. (2021)	x		x	x		x		x				x		x			x			x				x	
Lv et al. (2021)	x		x	x	x		x	x	x		x	x				x					x			x	
Huang et al. (2021	x		x			x	x	x					x	x	x	x				x					x

Ferreira et al. (2021)		x		x			x				x	x					x			x			x
This Paper	x		x	x	x	x	x	x	x	x		x	x	x	x			x	x		x		x

Table 1. Literature gap (Legend: CD: *Control Design*; TD: *Technology Design*; ID: *Interface Design*; SDA: *System/Application Design;* Ma*: Manipulation;* De*: Detection;* SM*: Separation Monitoring;* P&P*: Pick and Place;* T*: Throughput;* C*: Cost;* WS*: Worker's Skills;* Sa*: Safety;* Erg*: Ergonomics;* A*: Assembling;* M*: Manufacturing*; Pkg*: Packaging;* FPF*: Food Production Facility;* P*: Prototyped;* I*: Implemented;* Coe*: Coexistence;* Int*: Interaction;* Coo*: Cooperation;* Col*: Collaboration*).

2. Methodology

This section illustrates the architecture of the support-design framework of cooperative robot systems. While presenting the design steps in Figure 1, it describes the incorporated design tools and general working principles.

Figure 1 presents the framework as an iterative closed-loop procedure intended for system design and shows the interdependencies connecting design targets and levers. This framework evokes the pattern of the feedback control loop with noise on the exit (Zhang et al., 2013). The procedure's input consists of the design targets and the collection of data features significant of the environment. Such data feeds the block of the assessment, namely *Simulation and Assessing Methods* (SAM). SAM encompasses a broad and generic set of methods that allow defining and computing the performance of the current design solution. It mightly includes kinematic tools (Tang et al., 2021; Yang et al., 2019), digital twins (Jones et al., 2020; Koulouris et al., 2021; Malik & Brem, 2021b), CFD and stress analysis (Silvestri, 2021; Xia & Sun, 2002) when focusing on technical performance, rather than numerical simulation or operations scheduling tools to investigate the economic feasibility of the solution (Accorsi, Garbellini, et al., 2019; Musavi & Bozorgi-Amiri, 2017), or human-interaction tracking systems in case of safety and ergonomics evaluation (Amorim et al., 2021). Such performance is compared to the design target (i.e., *KPI**) within the *Comparison* block. The gap between the target and the current t-*th* measure (i.e., $\Delta K[t]$) feeds the *Re-design Methods* block assumed as the actuator of the feedback control loop. The corrections (feedback) trigger the configuration of a new solution and update input parameters to the SAM block. Thus, the framework iterates the procedure until the desired convergence is achieved. The remainder of this section provides examples and further details about the behavior and features that each block of the closed-loop method presents.

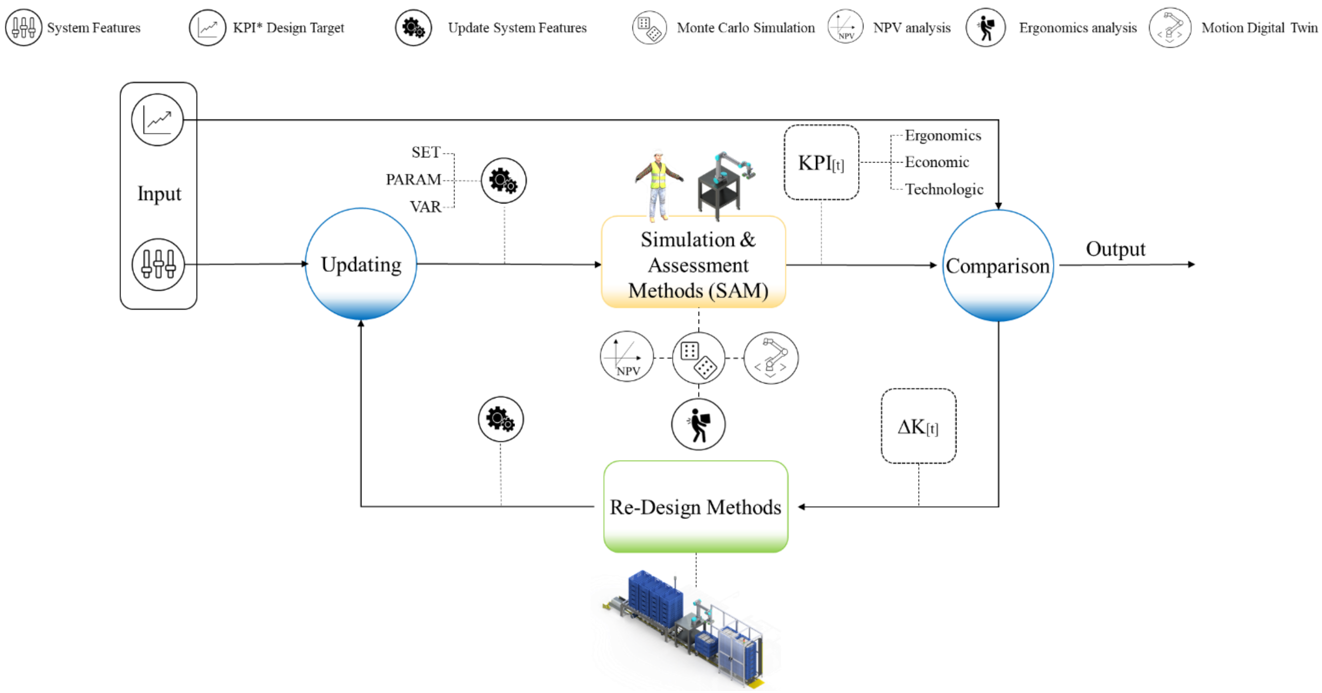


Figure 1. Iterative closed-loop methodology intended for system design.

2.1. Input or data collection

The definition of the input parameters is dependent on the type of processes observed. For instance, time and motion analysis provides the times spent by labor and machines throughout the operations organized in tasks and sub-tasks. Other information sources are the enterprise information systems and databases, available architectures of sensors of throughput and downtime, datasheets for the features and characteristics of the machines, and design parameters intended as targets coupling with normative, rules and standards (UNI EN ISO 10218-1:2012, UNI EN ISO 11228-3:2019). Despite the source, the broad set of data collected enables describing the as-is scenario and fueling the methods and tools of analysis embedded in the SAM block.

2.2. SAM phase

The simulation and assessing tools can vary depending on the driver adopted to reject an obtained solution. At this phase, the methods receive the variables from the input block. The results obtained with the application of these methods iteratively change. This procedure is iterated until the desired convergence is met.

Input quantities are organized as shown in Figure 2 (e.g., *SET*, *PARAM*, *VAR*) to feed various simulation models. Referring to the case study of Section 3, SET contains *resources* such as operators and Cobot, *task* (e.g., operations performed by the resource), *machine* (i.e., belt and roll conveyor, labeling machine, fork-lift trucks), and other entities to which the parameters are associated. One or more parameters are associated with each set as features or properties. Three types of parameters exist: F*eature, Performance,* and *Target*. Feature encompasses all those parameters representing the constraint for design, whilst performance includes the entities required to calculate the objective functions. Target parameters are the set-points and allow quantifying the errors compared to the current solution. For instance, a parameter named time exists for each resource, task, and machine set and belongs to the performance category. In a nutshell, the feature represents the input parameters of a solution (i.e., systems configuration), whilst the unknown performance for such configuration results from the simulation/virtualization conducted by SAM. As shown in Figure 1, SAM encompasses several methods that tally quantitative performance of the system. With regard to this research, we focus on economic, technical, and ergonomics aspects. Particularly, we use the Net Present Value (NPV) to benchmark the investment, OCRA and NIOSH indices to quantify ergonomics, motion control digital twin to prevent failures, and layout metrics to assess feasibility. Despite the implemented methods, SAM open to other tools.

The following subsection draws two examples of simulation and assessment methods implemented for the proposed case study.

2.2.1. Ergonomic analysis

Manual operations performed in manufacturing systems involve physical efforts and significant stress mostly affecting the upper limbs, shoulders, and low back. Manual material handling (MMH) of loads, awkward postures, and high repetitive movements are major causes for occupational diseases, such as cumulative trauma and Work-related Musculoskeletal Disorders (WMSDs) in manufacturing (Bevan, 2015; Colombini et al., 2001; EU OSHA, 2018; National Research Council, 2001; Padula et al., 2017). The International Standards Organization (ISO) provides information for designers, employers, and safety professionals involved in the design of work systems, tasks, and products, to design ergonomic workplaces and promoting the culture of safety at work. The ISO 11228 series of International Standards, the ISO 11226 (2000) and their application document, the ISO/TR 12295 (International Standard Organization, 2015), define a set of recommendations for performing safe manual handling operations. These standards also provide the risk assessment methodologies for hazard identification, risk estimation, and risk evaluation. Specifically, the ISO 11228 series addresses the ergonomic approach to manual handling activities like lifting and carrying (International Standard Organization, 2003; T. Waters, 1993), pushing and pulling (International Standard Organization, 2007a; Snook & Ciriello, 1991), and manual handling of low loads at high frequency (International Standard Organization, 2007b; Occhipinti, Enrico; Colombini, 2004). The ISO 11226 is the International Standard for evaluating static working postures, which provides the limits for static working postures with body angles and duration, and the minimal external force exertions (International Standard Organization, 2000). Finally, the ISO/TR 12295 defines additional criteria and details for applying the risk assessment methods proposed in the original standards of the series(International Standard Organization, 2000, 2015). These standards aim to address the application of ergonomics principles to workplace design and re-design. When recommended limits are not satisfied, corrective measures and risk control measures should be taken to prevent the risky operation or modify the working conditions and provide auxiliary equipment for risk reduction. After analyzing the work process and the manual operations performed in the workplace, employers and safety professionals must adopt the proper risk assessment methodology and ensure that manual handling activities do not expose the workers to some risks for their health and safety. The introduction of one or more collaborative robots in a manufacturing system does not exclude the presence of potentially hazardous work conditions. The ultimate aim of the HRC is the creation of perfect complementary between humans and robots for reaching higher features and performance that traditional manufacturing systems could not accomplish. In this context, the ergonomic analysis provides a quantitative measure of interaction quality between the workers and the robots, i.e., the HRC. The ergonomic risk assessment included in this study focused on the manual activities required to the workers before and after the introduction of collaborative robots in a manufacturing system. The aim was to verify the manufacturing system's ergonomic conditions and assess the quality of the HRC from an ergonomics perspective. The operations investigated in the ergonomic risk assessment in this paper include manual lifting activities and repetitive movements performed with the upper part of the body. The context in which manual operations are performed was investigated, together with the characteristics of the tasks and other risk factors related to work organization. The results provide a quantitative measure of the ergonomic risk for manual operations and priorities for improving the work conditions.

2.2.2. *Monte Carlo analysis*

Due to the high unpredictability that characterizes the performance of most system configurations, a canonical probability distribution can not readily assume. For each output variable, direct observation, test, and monitoring campaign result into samples to be analyzed. Monte Carlo methods can be used to extrapolate a behavior from such samples and generalize it through a probabilistic simulation of random events. The probability of such an event lies in the observed behavior of the sample. The adoption of Monte Carlo methods permits the simulation of a system configuration's behavior and estimates output performance as the handling/picking time, the idle time of the machine or the resource, or the throughput or safety of a specific system layout.

2.3. *Comparison*

The comparison step lies in the performance parameters assessed at the SAM block. This performance is compared to the target parameters (i.e., set-points), defined per objective function. The gap between the current performance and the set-point represents the error $\Delta K[t]$ at iteration t. Such error expresses quantitatively how the proposed solution approaches the desired values and provides the direction toward the improvement.

2.4. *Re-design method and update*

This phase includes a generic approach to re-design the current solution according to the improvement direction. This task can be manual or aided by a software application. First, the designer must set a new configuration of the system handling the levers of the input parameters/features. This way leads to a new solution which ideally corresponds to activate the binary variable of that configuration (i.e., $y_{tra} = 1$). The output configuration is designed via CAD and prototyping tools.

The update task is devoted to setting the new configuration's input parameters required to feed the SAM block at the next iteration.

3. Case study

A centralized industrial kitchen of the foodservice industry provides the proper testbed for applying the proposed support design framework. The centralized kitchen is a food production facility that satisfies broad customer requests regarding lost size and production mix (Penazzi et al., 2017). This production system is affected significantly by the technological cycles (i.e. recipes) and food processing/assembling tasks carried out. Hence, the optimal configurations of layout and equipment, tasks arrangement, and labor behavior are not generalizable and customized. The resulting complexity meets our support design framework.

3.1. Data gathering

The production system taken into account focuses on a single area of the industrial kitchen: the end-of-line intended for packing, labeling, and palletizing food portions. We gather data through direct (on-field) and indirect ways. Indirect ways encompass company databases, sketches and drawings, and previous monitoring campaigns. On-field records refer to the time and motion analysis, the hourly labor cost, the number of operators.

Once the portion is packed and sealed in a modified atmosphere-filled tray, the conveyor moves the tray to the end-of-line buffer, where an operator picks and places it into a reusable plastic container. The stack of containers filled by homogeneous trays constitutes the production batch/lot. The lots are moved to the refrigerated storage area employing special roll-containers, known as *dollies*.

Data collection refers to all the inputs or features defined within the System Features (SFs) and proceeds involving one set at once. Such features include the operations, the layout and the equipment, the costs.

According to the nomenclature of Section 2, the entities of the set C*haracteristic Operations* (CO) for the end-of-line are listed in Table 2. The parameters/attributes *Operation type*, *Number of workers*, *Time*, and *Weight* describe and characterize each CO. The *handling unit* suggests the physical load moved at that task. Other attributes, like worker's skills or requirements, could be added case by case. Table 2 reports the value of these parameters brought out from the on-field times and motions analysis.

CO n.	CO description/name	CO type	N. of workers	Handling Unit [u]	Working Time [s/u]	Weight [kg]
1	Lot settings	Manual	1	-	8 ÷ 13	-
2	Picking an empty container	Manual	1	Container	2 ÷ 4	1.8
3	Waiting for the reference to arrive	Automatic	1	-	V.T. [3÷158]	-
4	Labeling of reference	Automatic	0	Tray	1 ÷ 2	-
5	Picking of reference	Manual	1	Tray	1 ÷ 2	V.W. [0.1÷0.35]
6	Filling a case with reference	Manual	1	Tray	V.T. [33÷375]	-
7	Labeling of a full case	Manual	1	Container	2 ÷ 3	-
8	Drop an entire case on the roll container	Manual	1	Container	V.T. [4÷30]	V.W. [4.2÷10.2]

9	Moving the full roll container to the storage area	Manual	1	Dolly	V.T. [60÷240]	V.W. [43.6÷91.6]

Table 2. Characteristic operations (Legend: V.T.: Variable Time; V.W.: Variable Weight).

The parameters time and weight in Table 2 can be either deterministic or stochastic depending on the randomness of the specific task. Due to the high uncertainty that characterizes such operations, the on-field monitoring generates samples distributions instead of averages. We use the Monte Carlo method to extrapolate the stochastic behavior of each task in terms of operations time and ergonomic load, and occurrence analyses are carried out to the purpose. Figure 2 illustrates how the occurrence analyses feed SAM through the numerical simulation block. Upon the PDF (one per each task of the COs set), SAM runs a numerical simulation that generates a sensitivity analysis attempted to assess the performance of the current system configuration. For the case study, the economic and ergonomic performance are calculated through quantitative metrics and robot trajectories via a tailored motion digital twin.

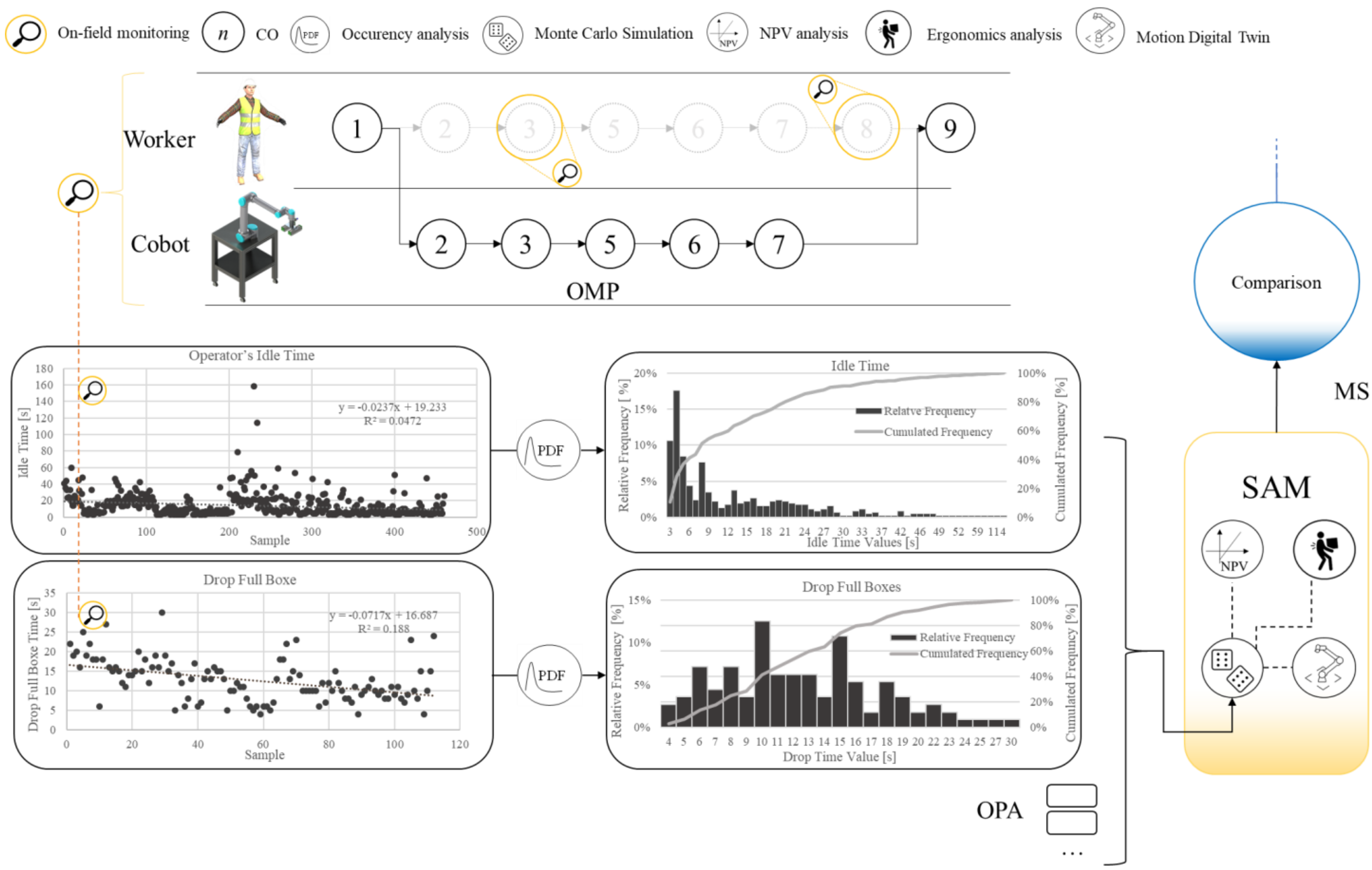


Figure 2. On-field monitoring, Occurrences analysis, and SAM feeding. (Legend: CO: Characteristic operation; OMP: Observed manufacturing processes; OPA: Other PDF analyses; MS: Methodology steps, related to Figure 1)

The parameters regarding the *equipment*, the *layout*, and the physical entities' *flows* are included within the System Feature named Layout. For instance, Tufano et al. (2018) provide the physical flows for the observed production system. These variables are essential to lead to new equipment selection. The as-is scenario shown in Figure 3 encompasses the existing equipment inside the layout, listed for reference in the Figure's caption.

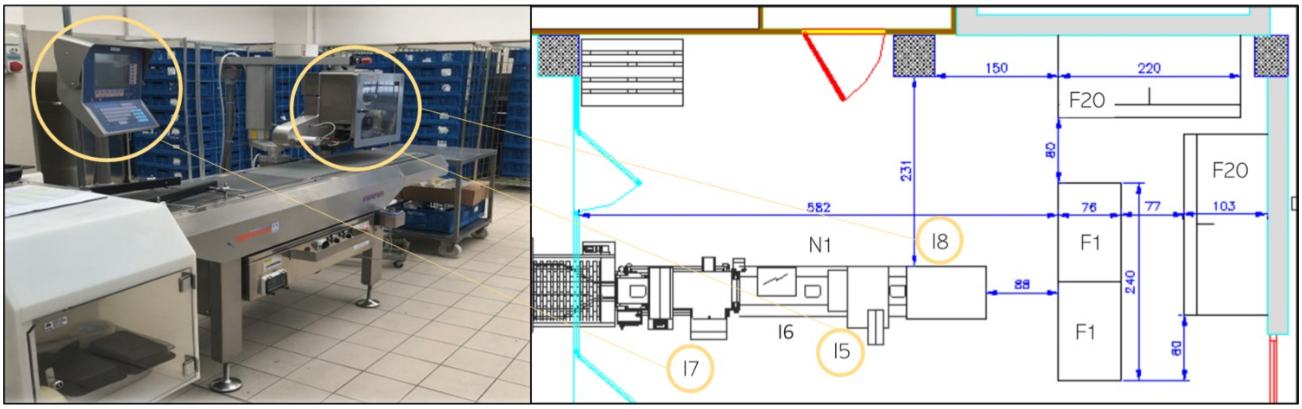


Figure 3. AS-IS layout. List of equipment: F1: Worktable; F20: Counter; I5: Labelling machine; I6: Load-cell; I7: CPU Terminal; I8: Labelling machine for full container; N1: Belt conveyor [quotes in centimeters].

The parameters *costs,* e.g., resulting from the labor and power associated with each CO, depending on the personnel's company policy and the energy mix that powers the production system. SAM uses these costs to assess the economic feasibility/performance of each system configuration.

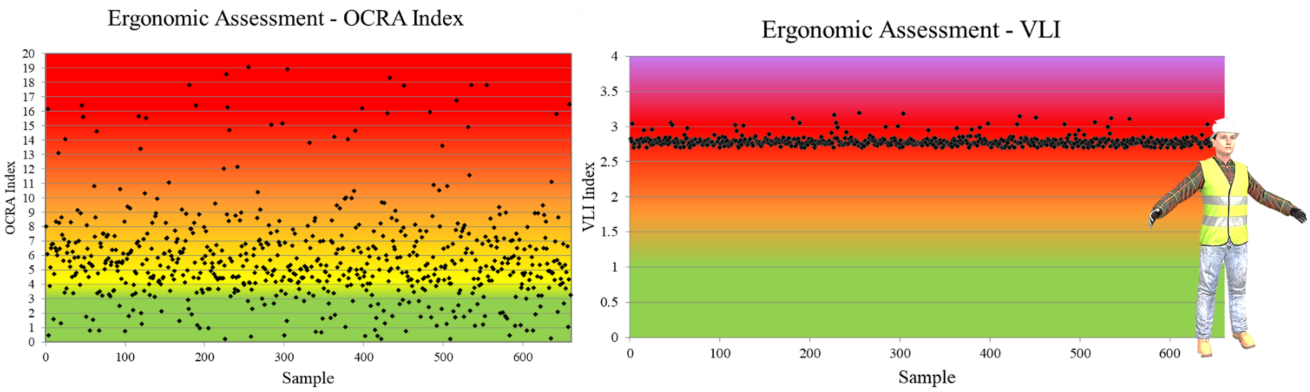
At the first iteration of the method, SAM calculates the performance corresponding to the current (as-is) configuration of the COs. In the case study, the economic and ergonomic performance are tallied. Regarding the financial side, no investments into new solutions correspond to a payback period of 0. Conversely, an accurate ergonomic risk assessment of the workplace is necessary, particularly for the manual handling operations performed during the manufacturing processes.

The ergonomic assessment paves the way for achieving ergonomic benefits by re-designing the current production system configuration. In this study, the COs that require manual handling operations are lifting and lowering tasks, e.g., trays picking and full-container handling into the dolly, and handling low loads at high frequency, e.g., picking and placing the empty containers. The methodologies adopted for the ergonomic risk assessment are in the ISO 11228-1 (International Standard Organization, 2003) and in the ISO 11228-3 (International Standard Organization, 2007b). Specifically, the ISO 11228-1 introduces the risk assessment methodology for lifting and carrying operations, with the Revised NIOSH Lifting Equation (International Standard Organization, 2003; T. R. Waters et al., 1994). The goal is to assess the risk arising from manual lifting/lowering actions by identifying the Recommended Weight Limit (RWL) and obtaining a risk index, i.e. the NIOSH Lifting Index. The weight raised by the operator should hopefully be lower than the RWL, which considers the context in which the lifting activity is carried out, such as gender and age of the individual, geometry, and weight of the object, frequency of lifting/lowering actions, and other parameters (T. Waters et al., 2016b). Similarly, the Variable Lifting Index (VLI) allows safety analysts to assess the risk of variable manual lifting activities when the task characteristics, e.g. weight and height of the products, vary during the work-shift (T. Waters et al., 2016a).

The second ergonomic assessment methodology adopted in this study is the OCcupational Risk Assessment (OCRA) described in the ISO 11228-3 (International Standard Organization, 2007b). Such methodology provides a quantitative measure for assessing the ergonomic risk due to handling low loads at high frequency, i.e. the OCRA index. Specifically, the OCRA index compares the actual number of technical actions (ATA) performed by the worker during the repetitive task, and the number of reference technical actions (RTA), for each upper limb, allowed in the work shift. The overall number of ATA is determined from the observation of the technical actions performed during the repetitive task. The number of RTA allowed in the same time slot is based on the analysis of the context in which the repetitive task occurs, including force exertions, awkward postures, and movements of the upper limbs, work organization, and a set of environmental factors such as, for example, the use of personal protective equipment that may interfere with handling ability, the requirement for accuracy, and the use of vibrating tools. This risk assessment methodology is commonly used in industrial research and in the field of Occupational Medicine.

Figure 4 shows the results of the ergonomic assessment for the as-is scenario. Using numerical simulation, SAM quantifies the ergonomic load along two years of production. Figure 4 plots the VLI index, which reveals the high risk for the workers involved and suggests timely re-design of tasks and workplace.

Against the business-as-usual, the proposed iterative methodology supports automatizing these tasks incorporating a collaborative robot into the production end-of-line.



OCRA Index	Tolerable	Low Risk	Risk	High Risk	Very High Risk
N. of Days	60	55	105	376	64
Relative %	9.1%	8.3%	15.9%	57.0%	9.7%
VLI Index	**Tolerable**	**Low Risk**	**Risk**	**High Risk**	**Very High Risk**
N. of Days	0	0	612	44	4
Relative %	0%	0%	92.7%	6.7%	0.6%

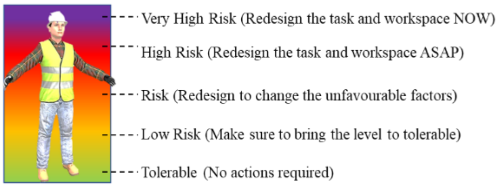


Figure 4. Ergonomic assessment.

The KPIs, namely *Design Targets* (as part of the System Feature), are claimed by the company or suggested by the state-of-art. For instance, Correia Simões et al. (2020) state that a crucial factor influencing automation is the *acceptance* i.e., concerns and expectations of the workers. The intention to automate a labor-intensive process line is interpreted as a pretext to narrow down personnel costs. In the case study, acceptance is encouraged by excluding workers' firing and ensuring to re-allocate them to different tasks to improve the acceptance. Some design targets are sum up in Table 3.

KPI	Value

Budget	35,000 [€]
Payback Period	< 24 [month]
Operators' skills	\
Regulation compliance	UNI EN ISO 10218-1:2012 UNI EN ISO 11228-3:2019

Table 3. Design target parameters.

3.2. Iterating the framework

Different systems solutions/configurations are designed whilst iterating the support-design framework. For each configuration, the features of the systems (SFs) are calculated or extrapolated.

For the case study, a first solution is explored in Accorsi et al. (2019). This section builds from then, and iterates the method to generate and compare new solutions. Table 4 samples some values of the gap parameter **ΔK** which measures, for each KPI and iteration, the distance between the current value and the set-point.

Iteration	Budget	Cost [k€]	Saving wrt Budget [%]	Payback Risk	Size [sqm]	Risk analysis	Ergonomic Index	Operators'skills
1	1	25	28.6	70%	4.80	0	Minor	Basic
…	…	…	…	…	…	…	…	…
t-th	0	45	-28.6	75%	5.34	1	Major	Basic
…	…	…	…	…	…	…	…	…
T	1	32	8.6	85%	3.82	1	Major	Basic

Table 4. Summary of ΔK values. (Legend: wrt: with respect to; 1: constraint achieved; 0: constraint unmet)

The integration of a collaborative robot into a consolidated labor-intensive process does not improve the operator's working conditions, either not supported by a layout revision (Rega et al., 2020). However, at the first iteration, some alternatives are overviewed. The comparison step (see Fig. 1) rejects the solutions which do not comply with the regulations and standards. The equipment considered for the following iterations consists of a collaborative robot (UR 10 – Universal Robots™) with ten kilograms of payload, a gripper with Venturi's effect working principle (KVG20060FR5 – Piab), and a customized movable aluminum table. This table is used as a support for the Cobot, the power unit, and the PLC.

After a certain number of iterations (at the generic t-th iteration), the output provides a first reliable layout. This configuration represents a technically feasible solution, although the budget constraints is not respected. Moreover, the risk analysis was not necessary because the solution breached one of the feature parameters. The solution shown in Figure 5 uses the main belt-conveyor coupled with an L-deviation to head trays to the Cobot. The buffer of empty boxes was a motorized roll-conveyor. This buffer communicates with the Cobot's PLC. Two rails connected to the rotating platform allow the ejection of the full dolly. The two rails allow separating the workplace where the dolly is empty or full, while the rotating platform allows orientating the dolly along the filling process. The rails-platform-based system is shown in the upper-left corner, whilst the plastic boxes buffer is in the lower right corner.

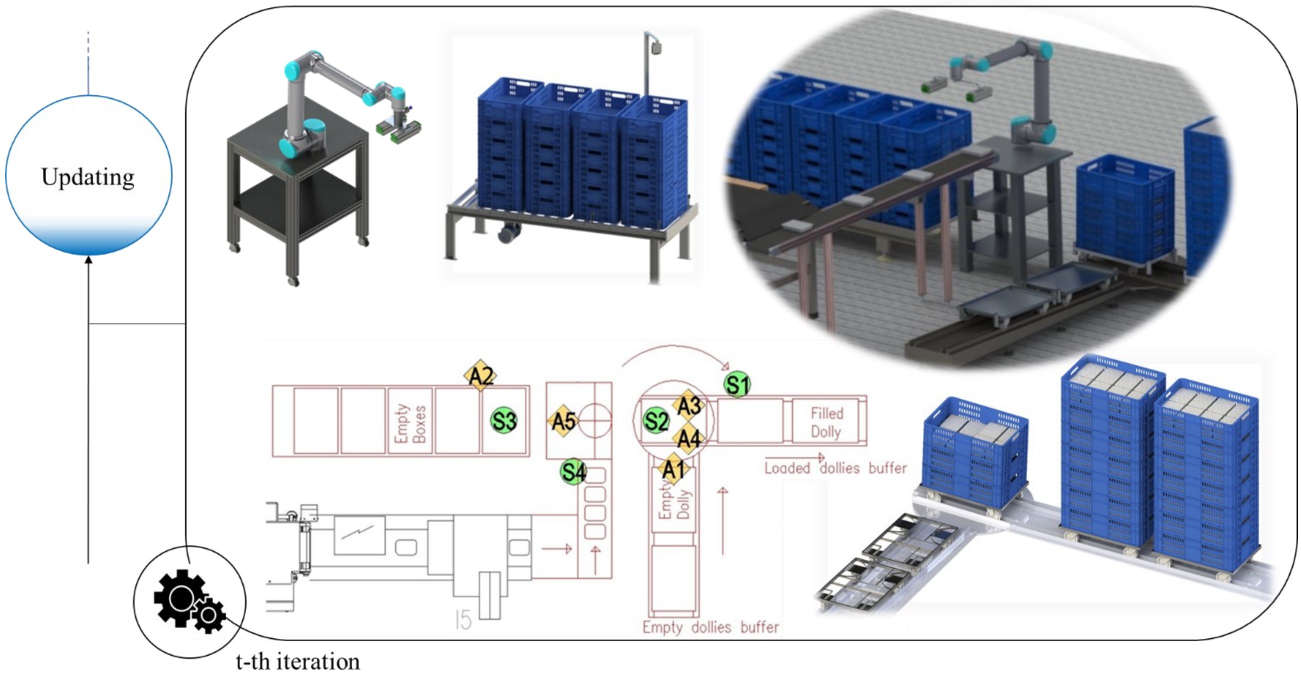


Figure 5. Solution of the t-th iteration.

The CAD layout allows an overview of all equipment and is used to develop the control logic. Indeed, the operating logic defines the functional components, e.g., sensors and actuators, rather than specific items. Table 5 represents a list of sensors and actuators with the reference of the task they are applied to.

Sensors	**Code**	**Task**
Light barrier photocell	S1	Check saturation of loaded dollies buffer
Light barrier photocell	S2	Check the presence of an empty dolly in the loading area
Distance measuring device	S3	Check presence and determine the size of empty boxes pile
Mechanical switch	S4	Check the presence of reference in the end-line
Actuators	**Code**	**Task**
Stopper cylinder	A1	Lock/unlock empty dollies
Stopper cylinder	A2	Lock/unlock empty boxes pile
Pneumatic cylinder	A3	Rotation of moving platform
Stopper cylinder	A2	Lock/unlock dolly in the loading area
Electric valve	A5	Allows compressed air inflow to the gripper

Table 5. Sensors and actuators list.

Table 4 provides the parameter ΔK for the "t-th" iteration. The discarded solution talks the decision-maker into considering an additional system feature parameter. This constraint refers to the compactness of the layout. The rotating platform is avoided by relocating the empty dolly below the empty cases buffer. This re-design sharply reduces the budget needed by the new solution together with the size of the end-of-line. Furthermore, cutting off the platform moves the buffer of containers closer to the conveyor belt.

Figure 6 draws the final solution (T-th iteration). In such a configuration, the buffer of the dollies and of reusable containers are overlapping. A slightly slanted tailored platform permits dollies to head to the filling place by gravity. The front end is horizontal, and the ground level is devoted to a buffer for the loaded dollies ready to be transferred to the refrigerated storage. A Plexiglas and aluminum structure surrounds this area to avoid potentially dangerous interferences with the operators. A sensorized door that alerts the system when operators enter the area is located at the end of the platform.

The buffer of empty plastic containers is designed as a motorized roll-conveyor at the t-th iteration and maintained till the end. This device is coupled with a tailored vertical support for distance measuring. Being able to measure the height of the batteries of empty cases allows a more robust pick operation.

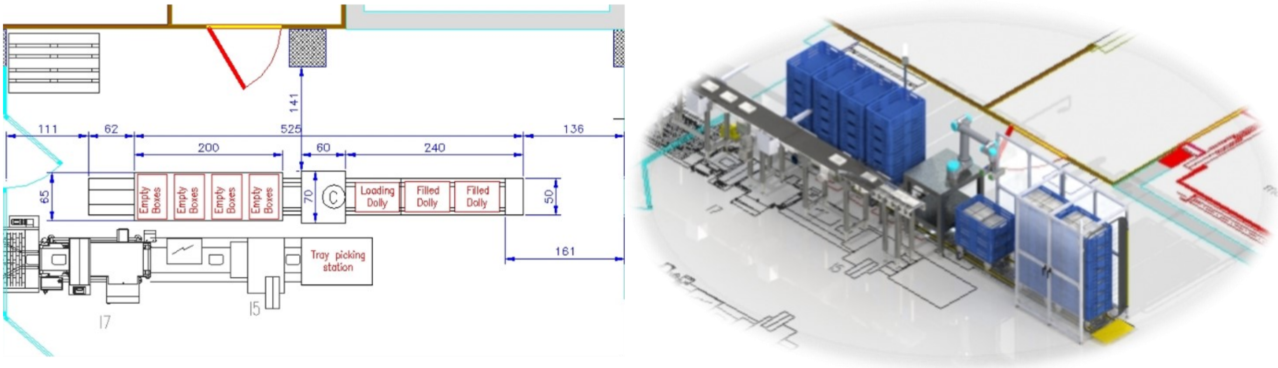


Figure 6. TO-BE layout

A small roll-conveyor with lateral barriers is placed at the end of the belt conveyor system. This equipment is implemented to drive and orient the incoming trays to a fixed picking position. The sensor for the nominal operation of the designed output end-of-line is shown in Table 6, whilst the acronyms refer to figure Figure 7.

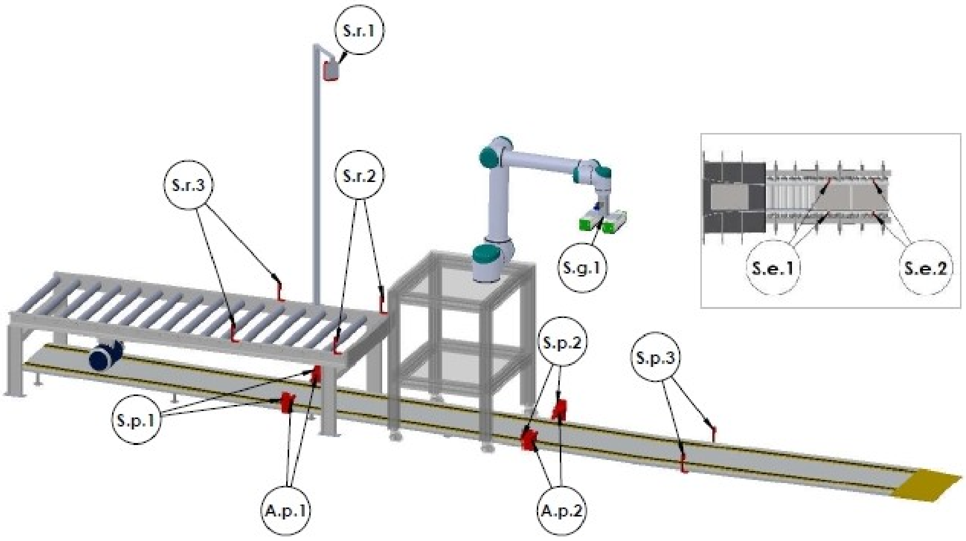


Figure 7. Layout of sensors and actuators.

Sensor	**Code**	**Task**
Suppressing background photocell	S.g.1	Check gripped object
Light barrier photocell	S.p.1	Check the presence of empty dollies
Light barrier photocell	S.p.2	Check presence dolly in the loading area
Light barrier photocell	S.p.3	Check space in filled dollies buffer
Light barrier photocell	S.e.1	Check the presence of references in the picking area
Light barrier photocell	S.e.2	Check the presence of references in the picking area
Light barrier photocell	S.r.2	Check presence empty boxes in picking position
Light barrier photocell	S.r.3	Check the presence of a spare empty plastic case pile
Distance measuring device	S.r.1	Measures height of boxes pile
Actuators	**Code**	**Task**
Stopper cylinder	A.p.1	Let flow a dolly in the loading area
Stopper cylinder	A.p.2	Let flow the filled dolly in the buffer
Electric valve	A.g.1	Activate/deactivate the grippers

Table 6. Sensors and actuators list and involved tasks.

The cobot PLC forbids communication via field bus. It uses instead a sensor that generates an output signal acquired from the command console. The sensors architecture includes some light barrier photocells (BALLUFF – 5K-NU-LX10-02), a distance measuring device (BALLUF – BOD 63M-LA02-S115), and a suppressing background photocell (BALLUF – BOS 12M-PA-RF10-S4). The cobot PLC generates digital output with 24[V] to control all the actuators propelled with compressed air. The final ΔK parameters are reported in Table 4.

3.3. Safety protocol

To implement a security protocol, we integrate hardware and software solutions. The Cobot PLC provides intrinsic standard safety and human-care functionalities. We develop further functionalities from scratch with the aid of dedicated sensors. Any signal received from a sensor links to an error code used to regulate the speed and acceleration of the robot's trajectories. We distinguish two main error categories. The first, namely *1-xxx,* triggers a robot's stop using the emergency brakes. The cell returns to the nominal working conditions only when an operator fixes the error and pushes the resuming pop-up on the control GUI. The second (*2-xxx*) triggers the reduced mode, which decreases the Cobot's speed and acceleration. The working cell returns to the nominal working conditions when an operator removes the error warning.

The support-design framework performs a risk analysis foreseeing different HRIs (Kopp et al., 2020) to make the cooperation between Cobot and man feasible. By highlighting the workspace and tasks shared between the Cobot and the worker, the designer avoids potential dangerous HRIs. In the case study, no collaborative operations (HRCs) are identified by the risk analysis. However, the worker could erroneously enter into the robot's workspace while persuing his tasks. In such a case, a laser scanner (SICK-S30A) detects the worker's presence and triggers a system error. This device allows monitoring the environment around the manipulator defining two risk areas. Each area, drawn as rectangles of different colors in Fig. 8, triggers a safety protocol affecting the speed and acceleration of the Cobot. When an operator invades the yellow area, an error of category 2-xxx is activated, and the cell continues to work at a reduced performance. However, when the operator crosses the border between the yellow and red area, a category 1-xxx error occurs, and the cell breaks down.

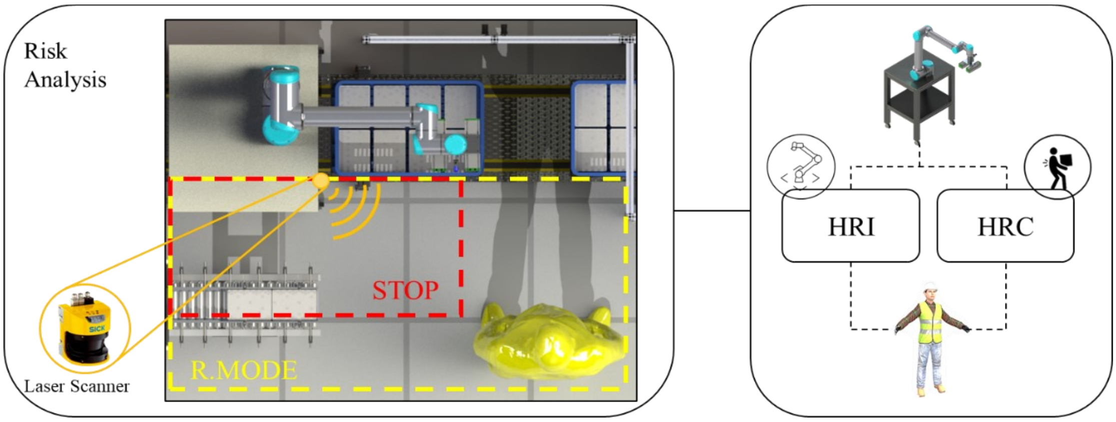


Figure 8. Security areas

To avoid accidental collision between the worker and the dolly a protective cage is prototyped. The structure is made of extruded aluminum profiles and equipped with gates. Each gate includes a magnetic sensor (BALLUFF - AG TK-52-CD/2) that detects when the door is open, incurring an error of category 2-xxx. Implementing these safety solutions reduces the working space of the Cobot as it must lie within the front area. The safety system depends on the layout and interaction between the robot and the worker, paying particular attention to the heavily congested zones.

4. Discussion

The literature analyses and the framework application aim to answer the research questions in Section 1. This paper underlines the constraints occurring along with the automation of labor-intensive manufacturing processes. Among these barriers, literature lists: i) technology, ii) cognitive, iii) safety and ergonomic, iv) throughput and performance, v) law and normative, vi) economic, vii) space and workspace (RQ1). Literature summarizes such barriers into leading performance metrics like (Hippertt et al., 2019) with HNR index, (Antonelli & Stadnicka, 2019) with their PFMEA, and (Costa Mateus et al., 2019) with the ergonomic indicators. Although such indicators lead the design of technically feasible automated solutions, a focused view of few performance metrics, neglecting the others, lacks addressing the rising demand for the integration of collaborative robots into labor-intensive manufacturing environments (L. Wang et al., 2019). The application of the proposed framework in a labor-intensive manufacturing process provides ergonomics benefits and cost reduction. The economic benefits result from avoiding injuries and musculoskeletal stresses due to repetitive tasks. We showcase that cost-saving does not necessarily result from the throughput improvement but occurs as a consequence of safety and ergonomics adjustments (RQ2). Specifically, the results of the ergonomic risk assessment for the as-is scenario in the food service facility investigated in this study revealed the presence of high risk for the workers involved in manual materials handling. These results also suggest that the high frequency of the movements performed with the back and with the upper limbs is the major risk factor of the manual operations. In this context, the incorporation of a collaborative robot assisting the workers during manual operations at the production end-of-line would improve the ergonomic conditions in which these activities are performed

This work handles several aspects of automating a manual production system and proposes a comprehensive framework that puts different digital twin tools to aid design (Guo et al., 2021; Lv et al., 2021). The illustrated case study shows how to apply the framework and how the digital twins are implemented to lead re-design. For instance, CAD allows evaluating the system layout, the workspace, and the zones of interactions (HRI). To achieve solution feasibility, CAD provides the overall size of each solution in order to comply with the available space. As shown in Table 4, the system layout occupies 3.82 [sqm], i.e., 40% less than the previous solution. The identification of the HRI that might occur during the tasks leads to re-design and deletion of some of critical processes avoiding collision. In the proposed solution we avoid handling empty boxes, saving the worker from lifting or lowering relatively high loads (RQ3). A Monte Carlo method simulates the performance of each configuration by tallying ergonomics, like the abatement from relevant ergonomics impact (NIOSH and OCRA) to almost zero (Figure 4). Simulation also underlines the decrease of capital cost of 23% from 45.000€ to 35.000€ within the threshold of the available budget (Table 4). Together these tools benchmark each system configuration and drive the fulfillment of the targets through an iterative approach.

The multi-disciplinary perspective of the framework characterizes each design solution with a set of indicators like production throughput, labor time and cost, worker's skills, safety, and ergonomics. To achieve the purposed result, we aid the decision-maker with a novel framework as a procedure intended for system design. Such a framework defines a feasible, affordable, and human-care solution using an iterative closed-loop methodology open to additional functionalities and tools. The multi-disciplinary perspective and the iterative approach are together strengths and drawbacks of this framework. While handling several dimensions at once, the designer must run and feed different digital twins with confidence, interpret the results, and enforce the gap reduction with the set point in the new configuration. Furthermore, the lack of integrated software involving all the digital twins into a unique platform makes the iterating procedure complex, rugged, and challenging. Thus, the limitation of this research falls within the lack of integrated and holistic tools able to carry out the design stages automatically.

Furthermore, given the broad disciplinaries and perspectives involved in this study, data entry would require a structured knowledge repository with variables and tables properly linked across the design steps. To the authors' experience, the available digital platforms and skills do not prevent such development. However, the lack of coordination and horizontal collaboration among designers and experts from different disciplines still limit the diffusion of such iterative design methodologies in industrial practice.

5. Conclusions

The ergonomic design of workplaces is a significant challenge of the Industry 4.0 revolution. Manufacturing processes and industrial systems are gradually changing their traditional layouts and configurations, preparing for the introduction of new technologies, as collaborative robots and exoskeletons. These technologies are not going to replace human workers in workplaces. Conversely, human assets will find support from innovative machinery and digital twin technology for improving the efficiency and the effectiveness of manufacturing processes. However, the digitalization of the processes and the introduction of higher levels of automation are driving the transition towards the development of new competencies and skills for designers, employers, employees, but also safety professionals and occupational physicians.

In this context, the active engagement and participation of human assets in each step of the Industry 4.0 revolution is fundamental for assessing the impact of smart technologies on process performance and users perceptions. Collaborative robots create a direct relationship with the workers. They share work operations, manufacturing processes, and work areas. Recent studies have extended the research on collaborative robots to the analysis of the ergonomics of the human-robot interaction, aiming to improve the usability of these technologies and the overall satisfaction of the users, i.e., the workers (Aaltonen & Salmi, 2019; Fletcher et al., 2020; Javaid et al., 2021; Kildal et al., 2018; Schmidbauer et al., 2020). Hence, the design of the factory of the future requires a holistic approach, aware of the importance of ergonomics and human factors, and focused on the improvement of both the system performances and the human-robot interactions.

The proposed framework aids re-design labour intensive manufacturing systems through feasible and affordable human-robot integrated processes. A closed-loop iterative methodology supports considering the system layout, the technology control, the financial aspects, the ergonomics benefits, and potential safety threats for the workers simultaneously. Applying this framework to the end-of-line of a food service facility results in a manufacturing configuration that respects the budget and payback constraint and complies with the regulations. While this framework is straightforward, its implementation requires open mind designers with multi-disciplinary skills. Future developments are then expected to develop a unique, integrated, and automated digital platform incorporating all the framework's steps at once under user-friendly GUIs.

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