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Digital Twin for Monitoring Ergonomics during Manufacturing Production

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Abstract: Within the era of smart factories, concerning the ergonomics related to production processes, the Digital Twin (DT) is the key to set up novel models for monitoring the performance of manual work activities, which are able to provide results in near real time and to support the decision-making process for improving the working conditions. This paper aims to propose a methodological framework that, by implementing a human DT, and supports the monitoring and the decision making regarding the ergonomics performances of manual production lines. A case study, carried out in a laboratory, is presented for demonstrating the applicability and the effectiveness of the proposed framework. The results show how it is possible to identify the operational issues of a manual workstation and how it is possible to propose and test improving solutions.

Keywords: ergonomics; manufacturing; production process; Digital Twin

1. Introduction

Ergonomic issues represent one of the main factors characterizing the manufacturing working environment. Indeed, in addition to designing a production system according to an ergonomic approach, the working activities need to be continuously monitored, especially when the volume of production varies, causing changes in cycle time and, consequently, changes in working tasks and workload.

Going more into detail, biomechanical overload represents one of the main risk factors in a manufacturing environment and is a possible source of Musculo-Skeletal Disorders (MSDs). MSDs consist in lesions or alterations of muscles, nerves, tendons and joints and, as demonstrated by numerous studies in literature and international standards, they are caused by prolonged exposure to awkward working postures, exerted forces, Material Manual Handling (MMH) and repetitive actions [1,2].

Over the years, the high incidence of the MSDs related to biomechanical overload led to the development of numerous risk assessment methods, principally observation-based, as collected by Takala et al. [3]. The application of risk assessment methods is mandatory during normal production to monitor working activities whenever changes are made to production volume or to working tasks. However, since the methods are observational, mostly based on the compilation of specific check-lists, the evaluation procedure is time-consuming and, additionally, strictly subjective, so it does not guarantee the repeatability of measurements.

For these reasons, in the era of Industry 4.0, the need to develop numerical methodologies and measurement devices has become a priority for companies wishing to have efficient and safe production systems. In particular, among the enabling technologies, the integrated use of Industrial Internet of Things (IIoT) and simulation tools allows for monitoring working performance, enhancing the control of the process and a near-real time management of the whole production line, in terms of balancing and ergonomics [4,5]. However, the literature dealing with the use of Industry 4.0 concept and tools for Ergonomics is poor, as also pointed out by Kadir et al. [6] in a deep review. Most researches are documented in conference proceedings, although the topic is very actual with wide application possibilities.

This research was born with the aim of creating tools that can support experts in ergonomic screening, ensuring accuracy and repeatability of measurements. From this point of view, the DT, based on the integration of IIoT and simulation, can represent the best solution as it allows exploiting the computational capability by using numerical models in which real data are implemented.

IIoT includes objects or devices (sensors, actuators, mobiles, etc.) that are able to interact and communicate between them, via internet protocols, and, thanks to the implementation of specific algorithms, they are able to carry out measurements and make decisions autonomously in order to manage machines and production systems [7]. Among these technologies, for ergonomics purposes, wearable devices are crucial since they can be provided with sensors capable to measure parameters related to humans (postures, forces, muscular activity, etc.). Widespread in recent years, wearable motion tracking devices have seen a massive introduction in the factory environment. Thanks to their good accuracy and low invasiveness, they allow acquiring motion data during normal working activities and analyzing them in order to evaluate ergonomics indexes related to the biomechanical load due to working postures [8–10].

In addition to IIoT, a manufacturing scenario can be fully reproduced in a 3D environment, giving the possibility to simulate the operations of a real working process [11]. This makes feasible, since the design phase, choosing the correct solutions, knowing in advance the performance of the line. The implementation of real data, collected by IIoT devices, in a simulation scenario realizes the so-called Digital Twin (DT).

Manual operations are still dominant in complex manufacturing systems [12], hence the working tasks are affected by high variability. By means of DT, it is interesting to investigate the possibility to implement real data into a simulation in order to assess ergonomics indexes.

In literature, several researches deal with digital human modeling and simulation for assessing ergonomics indexes. Caputo et al. [13,14] defined experimental/numerical procedures to evaluate the ergonomics of working activities by using, separately, inertial motion tracking system and simulation. Experimental data were used in Caputo et al. [13], for validating the numerical model, by comparing experimental and numerical results. The authors proposed a framework for preventively evaluating the ergonomic indexes (in particular, the Ergonomic Assessment Work-Sheet—EAWS) during the design phase of a new manufacturing line. In Caputo et al. [14], four ergonomic indexes, the same considered for the case study presented in Section 3, have been evaluated by means of numerical models for validating the design of a new workstation.

Makarova et al. [15] demonstrated that process parameters and ergonomics indexes can be investigated in a virtual environment. Case et al. [16] investigated the workers' ageing by implementing human capability data within a simulation environment. Tarallo et al. [17] proposed a computer-aided production control framework, which includes the use of digital human models, for implementing the principles of Industry 4.0 in manual working environments. The authors described how to monitor manual manufacturing processes by using a virtual simulation software (Siemens Tecnomatix Jack®) and an optical motion capture system (Microsoft Kinect®).

Sanjog et al. [18] used both physical and virtual ergonomics tool for assessing the ergonomics of an industrial shop-floor workstation. They pointed out that DHM and simulation could be very much beneficial for engineers/production supervisors/ergonomists to set the best design solution for a safe workstation.

However, these numerical models may not provide enough accurate results, since human motion is evaluated by inverse kinematic, making the movements sometimes unrealistic. So, implementing real data in Digital Human Models (DHM) should allow accurate simulation and assessment of production performance (ergonomics, working times, line efficiency, etc.).

Few significant studies have been documented in the technical literature about human simulation based on experimental data and most of them are relative to the control of human body for clinical purposes. Most of the research studies based on DT concern the improvement of manufacturing process and the product lifecycle management. In fact, there are no applications of human Digital Twin to assess the risk factors closely related to manual working activities.

Catarci et al. [19] provided a detailed literature about DTs and their modelling techniques, proposing a complex architecture for digital factories. Malik and Bilberg [20] presented a DT for investigating the performance of a human-robot collaboration work-cell, transferring the only data related to the robot, while Li et al. [21] developed an Augmented Reality (AR) application for the control of robots during a similar task, by implementing the DT of human hands by means of LeapMotion sensor and a Kinect V2 camera. Nikolakis et al. [22] used experimental data for the implementation of a DT for recognizing and simulating human activities.

Zheng et al. [23] studied the literature about DT technology for realizing a framework, aimed at product lifecycle management, based on three function modules: data storage, data processing and data mapping. Similarly, Ma et al. [24] proposed a framework based on DT to support the management of cyber-physical systems of production workshop, including product design and manufacturing. Aimed to improve the order management process, Kunath and Winkler [25] proposed a conceptual framework, based on DT, of a decision support system, which is able to find the best solution through simulating several scenarios. Instead, Havard et al. [26] combined DT and virtual reality in a co-simulation environment for assessing industrial workstations. They carried out a case study related to a human-robot collaborative workplace performing also ergonomic analysis.

This research aims to fill the gap in the literature about the use of human DT to evaluate ergonomics by proposing a methodology that supports ergonomists/occupational physicians/line managers in mapping the ergonomics risk for all the workstations of manufacturing environment.

There are two main motivations behind choosing a DT-based procedure for assessing the ergonomics. Firstly, it ensures that analyses are not affected by the ergonomist subjectivity, typical of the traditional (observational) techniques. Then, DT drastically reduces the computation times, thanks to algorithms able to quickly process data. So, since ergonomic analyses are significantly time consuming procedures, which could require hours for filling-in the spreadsheets, it is presumable saving a lot of time and then costs.

This paper moves from a previous research [4], in which the authors proposed a novel methodological framework, based on the implementation of a DT, for carrying out near real time analyses about the performance of manufacturing production lines, in terms of working times and balancing. The core of the research in [4] was related to human motion data collection and transferring for reproducing the real production in a simulation scenario. Such model is able to supply output data useful to the evaluation of the desired line performances, besides representing a predictive model for the behavior of the line itself following possible modifications.

Herein, the methodological framework has been modified and adapted in order to evaluate the worker's performance in terms of ergonomics, investigating the possible causes of risk of injury due to biomechanical overload: working postures, exerted forces, Material Manual Handling and repetitive actions. This procedure represents an innovation for the ergonomic screening of production lines that, currently, is still mainly performed by observational techniques and is a highly time consuming process. In fact, typically the ergonomist observes and records the work activity, estimates the index calculation parameters, fills in the checklists and evaluates the risk index. This process may require a significant amount of time, in the order of hours, to estimate the indexes of each workstation. In addition, the use of experimental data and DT allows an objective analysis as well as ensuring the repeatability of measurements. This approach contributes to the transformation towards the so-called smart factory, in agreement with the principles of Industry 4.0.

A case study, aimed to demonstrate the effectiveness of the framework, has been set and performed at the Laboratory of Machine Design of the University of Campania Luigi Vanvitelli. Data have been acquired by means of a wearable inertial motion tracking system [27] and the DT has been implemented in the Tecnomatix Process Simulate software by Siemens®.

The reminder of the paper is organized as follows. Section 2 describes the methodological framework, aimed to support the ergonomic assessment of the investigated working activity. Section 3 describes the case study that investigates an assembly activity reproduced in laboratory. Section 4 presents the results analysis and the discussions, while Section 5 concludes the paper.

2. Methodological Framework

Figure 1 describes the methodological framework developed to investigate about ergonomics of manual working tasks in a manufacturing scenario.

As already mentioned, the methodological framework moves from that one described in Fera et al. [4], which was related specifically on production line performance evaluation, whereas in this paper it has been modified and adapted for assessing the ergonomic indexes during the real production.

The framework consists of seven steps:

1. **Theoretical ergonomic balancing**: it is known and defined during the design and engineering phase of the production line;
2. **Production**: the workstation is selected for the investigation;
3. **Data collection**: experimental data about movements, forces, etc. are collected in order to allow the ergonomic evaluation;
4. **Simulation**: data are transferred to a DHM and the working activities are reproduced. Depending on the used devices, the simulation can be performed in real/near-real time or as post-process;
5. **Ergonomic assessment**: output data from simulation are used to evaluate the desired ergonomic indexes. In case the low risk condition is not satisfied, it is necessary to investigate and figure out the critical issues;
6. **Proposal and testing of improving solution**: critical issues need to be solved for satisfying the low case condition requirement. A time-based simulation is used for numerically testing and approving the proposed improving solution;
7. **Continue the production**: once the assessment is completed or the workplace is changed according to the proposed solution, the production can continue. A loop closes the framework, as the ergonomic mapping of the line has to be done every time there are changes in the production volume.

In the next paragraphs of this section, each phase will be explained and characterized. Data collection and simulation phases are the same of those described in [4], and briefly summarized in the following.

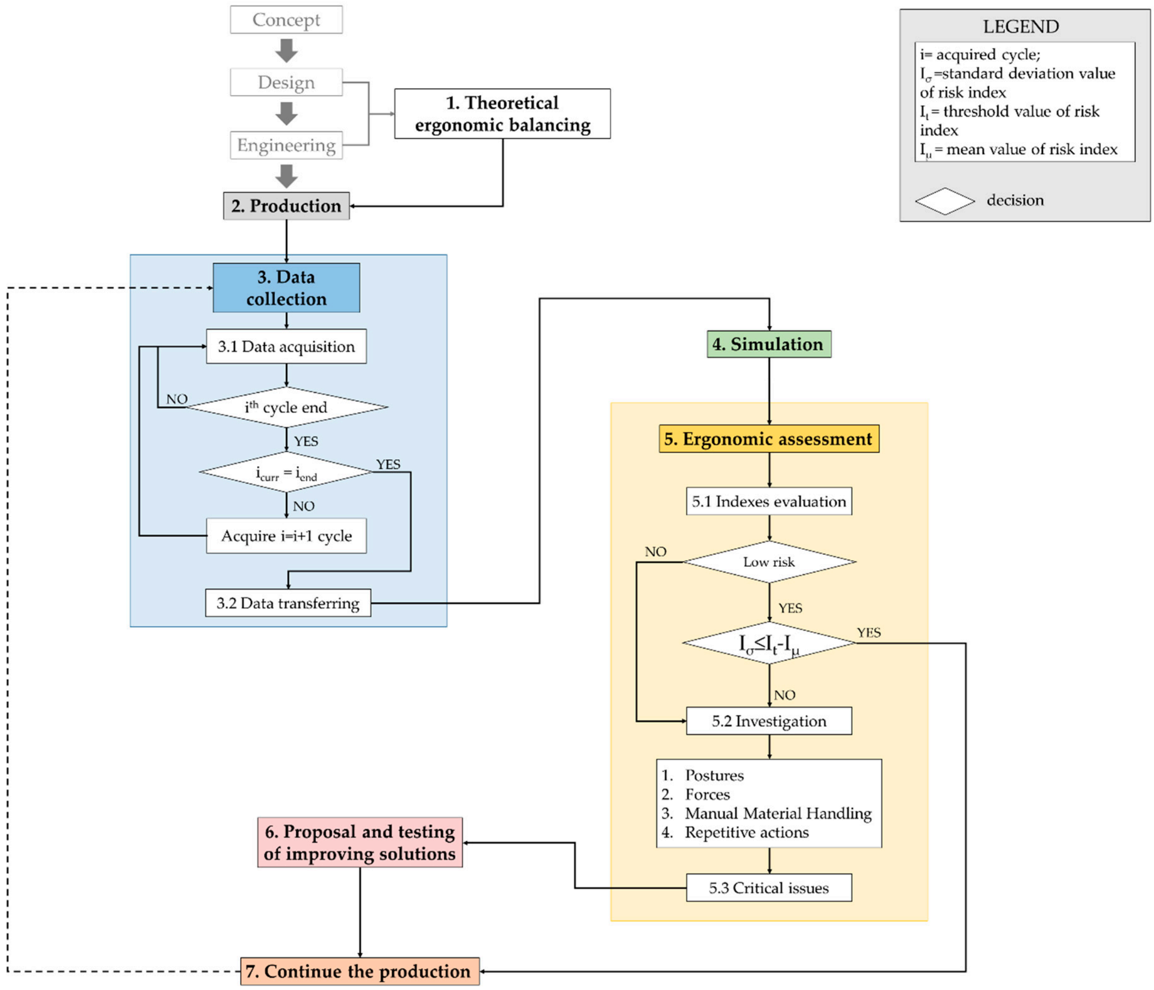

Figure 1. Methodological framework for monitoring ergonomics performance during the production process.

2.1. Data Collection

According to Fera et al. [4], data collection is a crucial step in order to apply the proposed approach. Specifically, data collection is related to the human body movements and it may be performed by means of both optical and non-optical motion capture based systems.

Together with the motion tracking system, it could be useful also to get additional data, such as the ones related to the exerted forces, by means of specific devices (force sensors, cyber gloves, etc.) to carry out the analysis.

It is important to define the number of cycles to be acquired during data acquisition session. This is required (see Section 3.1) in order to compute the basic statistical moments (mean and standard deviation) of ergonomic indexes, useful to assess whether a deep investigation is needed to evaluate critical ergonomic issues. The number of cycles to acquire during data collection phase strictly depends on the cycle time of the working task: in particular, the smaller the cycle time, the greater the number of acquisitions will be due to the increase of the variability of acquisitions [28].

Once the number of cycles to acquire have been defined, data acquisition session may start. If data acquisition is performed by means of wearable sensors, ethical requirement must be signed by the workers wearing them. Typically, a questionnaire about the usability of the system is also submitted to workers.

Acquired data are transferred to an appropriate software able to perform human simulations, such as Tecnomatix by Siemens® [29] or Delmia by Dassault Sistèmes® [30], and able to integrate such a data to the DHM, which accurately replicates the real workers' working tasks. Depending on the type of device used during the acquisition session, the way to transfer data to the software changes. In some cases, as shown later on in the case study, custom plugins and a re-sampling of data are necessary to integrate them in the simulation scenario.

2.2. Simulation

Step 4 in Figure 1 concerns simulation. Since it is focused on ergonomic assessment, simulation has to accurately replicate manual working tasks, according to the acquired data.

The steps [4] to follow in order to carry out the simulation are substantially four and involve: (i) virtual scenario setting, reproducing the same workplace layout; (ii) DHM creation, according to the anthropometric characteristics of the real worker; (iii) data implementation and operation refining when necessary (e.g., handling, picking or grasping an object, application of a force, etc.); (iv) run the simulation.

2.3. Ergonomics Assessment

Once the simulation is completed, numerical data are analyzed in order to perform the ergonomics assessment (step 5 in Figure 1). In a manufacturing scenario, as anticipated in Section 1, it is necessary to investigate the biomechanical overload, a source of injury risks, that is principally caused by working postures, exerted forces, MMH and repetitive actions with upper limbs. Many methods, tools and screening procedures have been developed over the years [3], some of which already implemented in different software codes for production process simulation. Many of them are according to the standards ISO 11,226 [31] and ISO 11228-1,2,3 [32–34] that regulate the whole procedure of occupational ergonomics monitoring.

After selecting the four risk indexes (one for each risk factor), numerical data are used for evaluating them (step 5.1 in Figure 1) for each acquired cycle. If the average values of the four indexes fall within the low risk area, the control phase is carried out by applying the following Equation (1) to each evaluated index:

$$\mathrm{I}_\sigma \leq \mathrm{I}_\mathrm{t} - \mathrm{I}_\mu \tag{1}$$

where I_μ and I_σ are the average and the standard deviation values of the evaluated index respectively, with respect to investigated working cycles, and I_t is the threshold value of the index for accessing the medium risk area.

If Equation (1) is satisfied, the framework suggests continuing the production (step 6 in Figure 1).

If none of the indexes fall within the risk area or if the Equation (1) is not satisfied, it is necessary furtherly investigating about the working task focusing on the critical factor.

This important step should be conducted by experienced ergonomists or by occupational physicians, since they have the appropriate know how for a proper identification and resolution of the critical issues.

Let us analyze in detail about the investigation (step 5.2 in Figure 1).

In case the working posture risk index does not fall within the low risk area, it is advisable to investigate, by observation or by studying the temporal history of postural angles, the postures assumed by the operator, identifying the sub-phases of the work cycle that mostly contribute to the value of the index.

About the exerted forces, if these exceed the maximum applicable value, as reported in specific tables by Snook and Ciriello [35], it is necessary to investigate the posture assumed during the force exertion, as well as the intensity and the duration of the application.

MMH is evaluated when the weight of the handled object is at least 3.5 kg; if the risk index exceeds the low risk area threshold, the investigations are different, depending on the kind of handling:

- for lifting operations, the attention has to be paid to the initial and final altimeters of the handling, as well as the type of gripping and frequency;

- for maintenance and carrying, the focus has to be on the distance travelled by the operator, together with the type of grip and frequency;
- for pushing/pulling actions, the investigation will be focused of the type and on the characteristics of the adopted cart, the distance covered by the worker and the frequency.

If the threshold value is exceeded by the index related to repetitive actions with upper limbs, the investigation will be focused on the number of technical actions, the possible awkward postures of the joints, the types of grip, the frequencies of actions and the recovery times.

Once the critical issues (step 5.3 in Figure 1) have been identified, it is advisable to discuss the possibility of making changes to the station layout or to the operations to be carried out.

After the discussion and testing of possible solutions, by means of numerical simulation, the ergonomist will deal with the decision-making process (step 6 in Figure 1) in order to improve the production process.

3. Case Study

Aiming to show the applicability and the effectiveness of the framework depicted in Figure 1, a case study is described here, related to a working task carried out in a laboratory, where a simple assembly task has been defined and performed. Figure 2 shows the working scenario reproduced in a simulation environment.

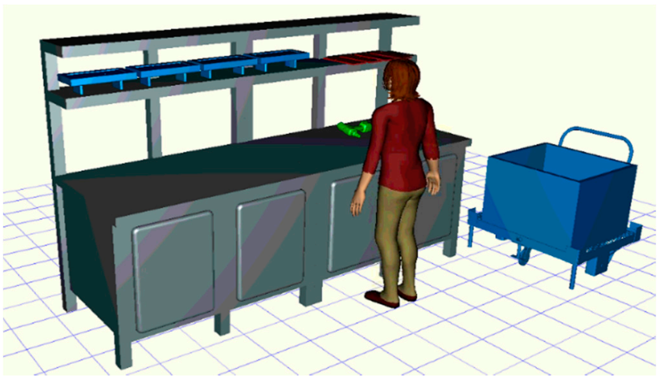

Figure 2. Workstation layout, reproduced in a simulation scenario.

As described in Figure 3, which shows both the real experiment and the Digital Twin, a female worker manually performs an assembly task of two components (labeled "1" and "2") made of steel. After picked up and positioned the components, these are joined by performing four screwings; then, the assembly is placed in a cart. A detailed description of each operation in reported in Table 1.

The assumed cycle time is 30 s, which includes 2 s of recovery. In addition, the work-shift duration has been assumed equal to 8 h, including 30 min breaks (10 min per break), equally distributed along the whole shift. A 60 min lunch-break has been scheduled at the middle of the shift.

Going into detail about the characteristics of the workstation, the components 1 and 2 have weight equal to 6 kg and 2 kg respectively, while the weight of the screwdriver is 2.5 kg.

About the screwings, the joints are made with M10 threaded bolts and the tightening torque is equal to 30 Nm.

The shelf where the two components are placed is 1400 mm high, while the height of the workbench is 900 mm. Finally, the assembly is positioned in the cart on a support plane 500 mm high.

The worker is P40 of the Italian female population [36], with a stature of 1550 mm and a weight of 45 kg.

In the following sections, the application of the methodological framework depicted in Figure 1 is applied.

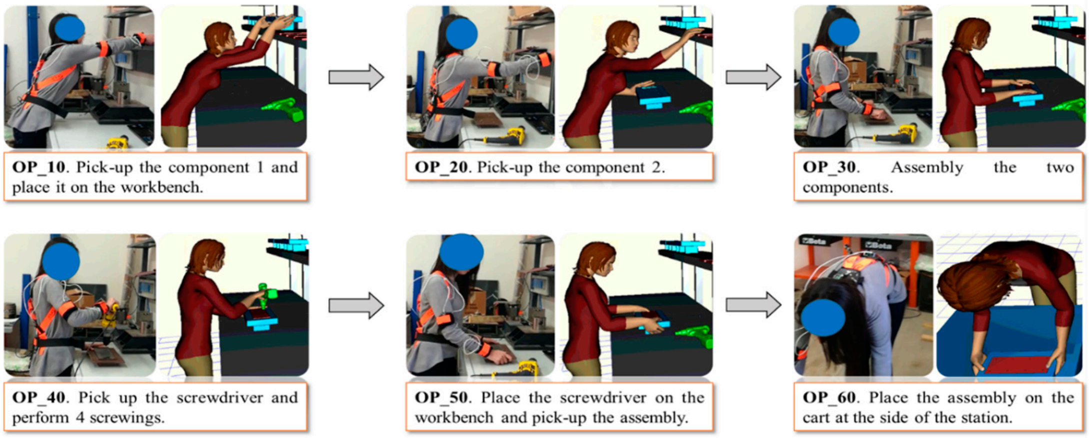

Figure 3. Tasks of the working activity. For each picture frame, on the left the real scenario and on the right the Digital Twin.

Table 1. Working cycle activities description.

Working Activities	
Operations	**Descriptions**
OP_10	The worker picks up the component 1, initially positioned on the shelf, with both hands, and then places it onto the workbench
OP_20	The worker picks up the component 2 from the shelf, with right hand, and places it above the component 1
OP_30	Matching the holes for the joining, the worker inserts and slightly turns four screws
OP_40	The worker picks up the screwdriver with right hand and performs four screwings
OP_50	The worker places the screwdriver on the workbench and picks up the assembly with both hands
OP_60	The worker reaches the cart at the side of the workstation and places the assembly

3.1. Data Collection

Motion data have been collected by using a wearable inertial motion tracking system developed at the Department of Engineering of the University of Campania Luigi Vanvitelli. The tracking system is composed by Inertial Movement Units and a sensor fusion algorithm, based on Extended Kalman Filter, has been developed for evaluating the attitude of body segments and, therefore, the posture angles related to the investigated working activity. Acquisition start and stop are managed by means of a mobile app used by an observer. A scheme of the motion tracking system is provided in Figure 4 and a full description of the algorithm can be found in [27]. This motion tracking system does not yet work in real time, so data transferring has been carried out after data processing. Indeed, the algorithm autonomously compiles CSV (Comma-Separated Values) files in which Euler angles, quaternions and posture angles are provided for each segment of the human body in each time frame.

The system is worn over the normal clothes by the worker (as in Figure 3) and, after a proper starting calibration of the sensors, the acquisition is run and the worker can normally perform the working tasks.

According to Giacomazzi [28], since the cycle time is about 30 s, motion data have been acquired for 60 consecutive working cycles (i = 60). Triggers have been manually introduced by the observer during the acquisition of data, in order to separate data related to consecutive working cycles. Figure 5 shows the trends of posture angles for trunk, elbow and arms along one working cycle.

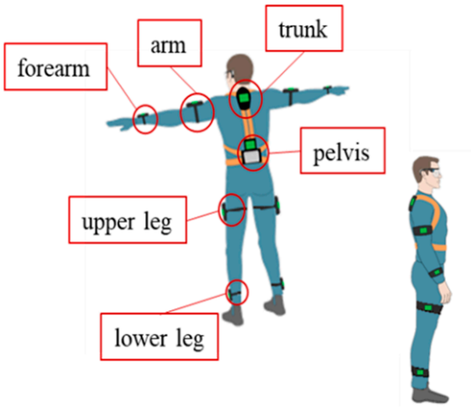

Figure 4. Wearable motion tracking system configuration.

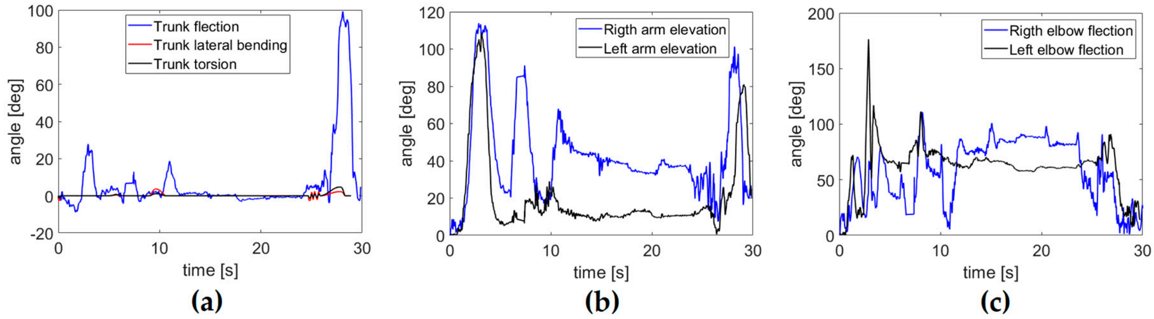

Figure 5. Posture angles trends over one working cycle for: trunk (**a**), arms (**b**) and elbows (**c**).

3.2. Data Transferring and Simulation

Data transferring is strongly influenced by the software chosen to perform simulation. Among commercial software for human simulation, most of them have interfaces that enable them to directly connect external supported devices, such as Kinect® or XSens®, to the simulation environment. Alternatively, several software packages allow implementing customized plugins to read data from external devices. To simulate the proposed working activity the software Tecnomatix Process Simulate by Siemens®, version 15.0.1, was used. It is an excellent solution for industrial processes simulation, including a module of human simulation which allows performing very accurate simulation of manual tasks. Moreover, several codes able to evaluate ergonomics indexes are already implemented and it is also allowed creating customized routines to implement other codes, plugins or interfaces. In this regard, a custom plugin has been developed in Visual C# to load the collected data. The plugin allows reading data stored on a CSV file, transferring them to the DHM and, hence, creating compound operations, according to experimental data, by using the function "CreateHumanCompoundOperation".

The pseudocode for data transferring can be found in Fera et al. [4].

For this study, data have been re-sampled in order to reduce the number of micro-operations and, hence, the computational cost. Figure 6 shows the interpolating curve of the sampled data related to the posture angles trends, shown in Figure 5.

Motion data related to all the 60 investigated working cycles have been transferred and, hence, all the working cycles have been simulated.

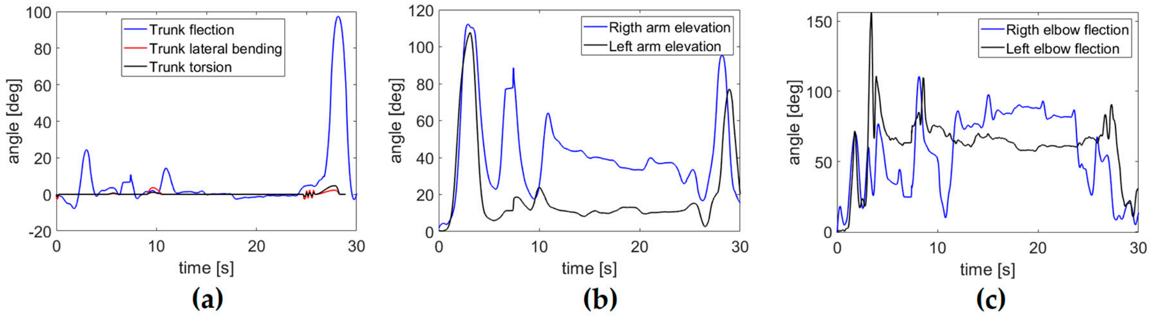

Figure 6. Posture angles smooth trends over one working cycle for: trunk (**a**), arms (**b**) and elbows (**c**).

3.3. Ergonomic Assessment

At the end of the simulation, numerical data are analyzed to perform the ergonomic assessment. As stated in Section 2.3, the main sources of injury risks are postures assumed by workers during each cycle of the work shift, exerted forces, MMH and repetitive actions; thus, each of this class has to be investigated by means of different ergonomic assessment methods.

In this case study, the methods chosen to evaluate each ergonomic category are the most feasible considering the type of working activity performed. They are listed below, with a short description:

- Working Postures: OWAS (Ovako Working Analysis System) method. It allows evaluating the whole body postures [37]. The method consists in the analysis of the posture to which a risk class is assigned, based on the values of postural angles. There are four classes (no risk, low risk, medium risk and high risk respectively) The index (I) for the whole cycle is evaluated according to the frequency (a, b, c, d) with which the four risk classes are found by means of the following equation:

$$I = [(a{\cdot}1)+(b{\cdot}2)+(c{\cdot}3)+(d{\cdot}4)]{\cdot}100 \quad (2)$$

- Manual Material Handling: NIOSH (National Institute for Occupational Safety and Health) lifting equation, which is useful when manual lifting of loads is carried out [38]. The method is applied only if the weight of the handled object is higher than 3 kg. It assigns a score based on the vertical and horizontal displacements with which the object is handled, as well as the frequency of action and the type of grip. The Lifting Index (LI) is given by the ratio between the Loaded Weight (LW) and the Recommended Weight Limit (RWL):

$$LI = LW/RWL \quad (3)$$

  where RWL depends on: worker's genre and age, vertical displacement of the object, maximum horizontal distance between the object and the body, angular dislocation of the object with respect to the sagittal plane, grip mode and lifting frequency;
- Repetitive actions: OCRA (Occupational Repetitive Actions) checklist, which is used to evaluate the biomechanical overload of upper limbs related to repetitive actions [39]. The checklist assigns a score based on the number of actions, fatigue (Borg scale), incongruous shoulder and wrist postures, type of grip, work organization, etc.;
- Force: in order to evaluate forces, a Force Solver based on Snook and Ciriello tables [35] was used. The tool provides the maximum force that can be exerted with respect to the posture assumed and the direction of application.

Table 2 reports the risk areas for the selected indexes.

Table 2. Risk areas for the selected indexes.

Index	Range Values		
	Low Risk	**Medium Risk**	**High Risk**
OWAS	<200	201–300	301–400
NIOSH	≤0.85	0.86–0.99	≥1
OCRA checklist	≤11	11.1–22.5	>22.5

It is worth noting that Equation (1), needed to perform the control phase of ergonomic indexes, is not applicable to all the chosen methods. In fact, Equation (1) is applied only when the index has a variability during the investigated cycles.

In this application, OWAS and OCRA indexes present variabilities along the working cycles, since fatigue, distractions or other factors may principally affect the working postures assumed by the worker; in contrast, exerted forces and NIOSH indexes remain the same in different cycles, since they depend on the positions of objects and on their weights, which are not variable.

3.3.1. Indexes Evaluation

In this section, the indexes evaluation is presented. The indexes have been evaluated by means of tools implemented in Tecnomatix Process Simulate, except for the OCRA checklist which has been filled-in by using data provided by the simulation.

Figure 7 shows the results concerning the OWAS index evaluation.

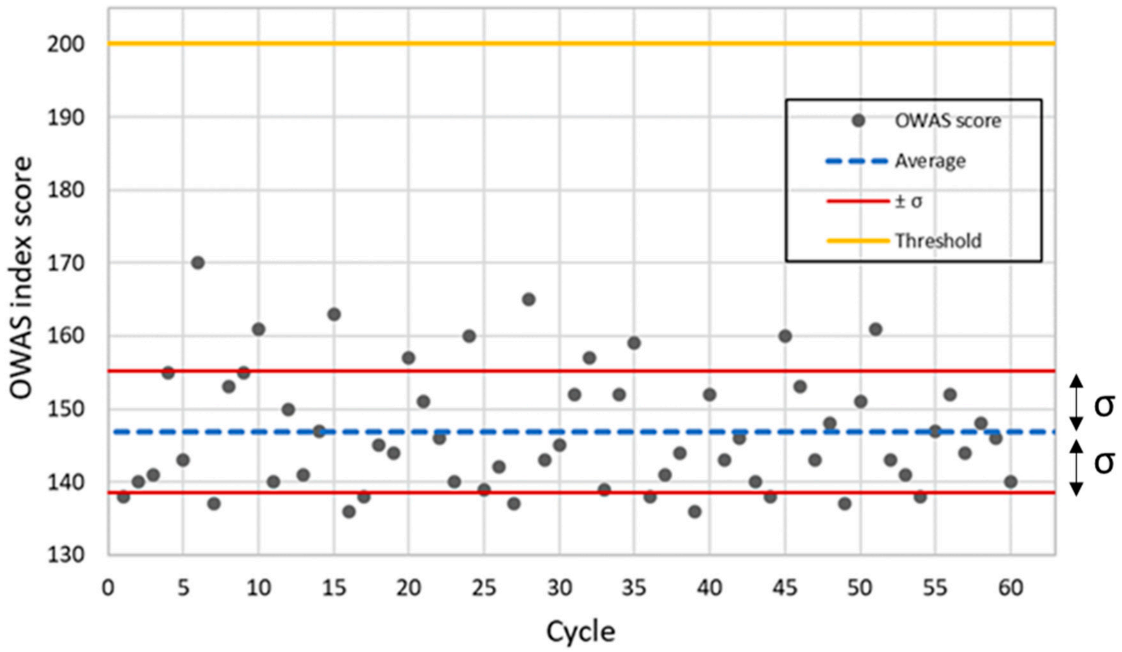

Figure 7. OWAS index scores for each working cycle and their statistical values.

The blue dotted line represents the average value of the OWAS index (I_μ), while red lines represent the standard deviation $\pm\sigma$ (I_σ) values. Table 3 resumes the statistical values and their comparison with medium risk threshold value (I_t).

Table 3. OWAS index score: statistical values.

	Average (I_μ)	**Standard Deviation (I_σ)**	**Medium Risk Threshold Value (I_t)**
OWAS index	146.9	8.3	200.0

By applying the Equation (1), it is possible to deduce that, as well as demonstrated by the results in Figure 6, it is widely verified:

$$I_\sigma = 8.3 < I_t - I_\mu = 53.1 \tag{4}$$

Thus, no further investigations are needed about working postures.

Regarding exerted forces, there are 4 operations that require the application of force. They are related to screwing operations (OP40 in Figure 3): the worker applies a counter-reaction force at the tightening end. The value of the force is the same for each screwing and in each working cycle, so there is no variability. It depends on the tightening torque (T), which is 30 Nm, and the lever arm (a), which for the used gun screwdriver (Figure 8b) is 100 mm. So the exerted force (F_{EX}) is given by the following equation:

$$F_{EX} = T/a = 300\ \mathrm{N} \tag{5}$$

The Force Solver tool in Tecnomatix Process Simulate enables to evaluate the maximum applicable force, based on the posture and on the direction of application.

Since it is not possible to predict the direction of the tightening end force, the worst-case scenario has been considered, which corresponds to the direction, in the transverse plan, along which the minimum value of the maximum applicable force is depicted (Figure 8a). The maximum applicable force is equal to 44 N.

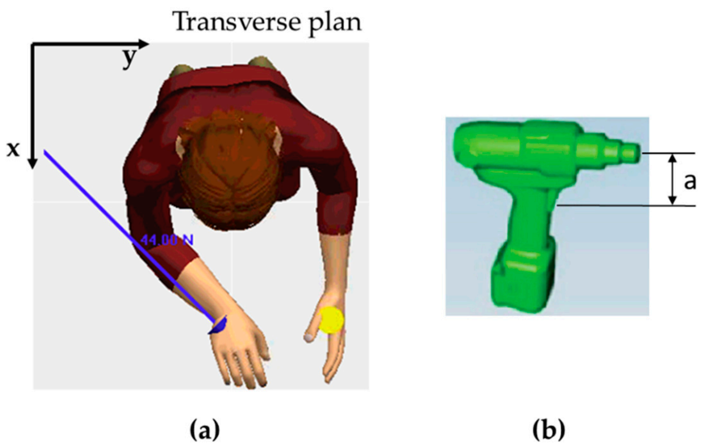

Figure 8. (**a**) Maximum applicable force. (**b**) Screwdriver lever arm.

Hence, the exerted force (F_{EX}) is widely higher than the maximum applicable force, so an improving solution is necessary.

Concerning MMH, NIOSH lifting index (LI) has been evaluated by considering two lifting operations that are performed for each task:

1. The first lifting regards the component 1, which has a weight of 6 kg. The heights of initial and final positions are 1400 mm and 900 mm respectively and the vertical displacement represents the main contribute to *RWL*. This component is handled with a frequency of 1 per cycle, thus during the work shift, a total of 900 components are lifted;
2. The second lifting concerns the assembly, which has a weight of 8 kg. The heights of initial and final positions are 900 mm 500 mm respectively. In this case, the main contribution to *RWL* is given by the maximum distance between the object and the body, which is equal to 400 mm. The frequency of handling is 1 per cycle too.

The NIOSH Lifting Index (LI) is constant throughout the working cycles and it is equal to:

$$LI = 0.96 \tag{6}$$

Concerning OCRA checklist, the scores varies along the cycles. Figure 9 shows the results concerning the right limb, which is the most stressed one.

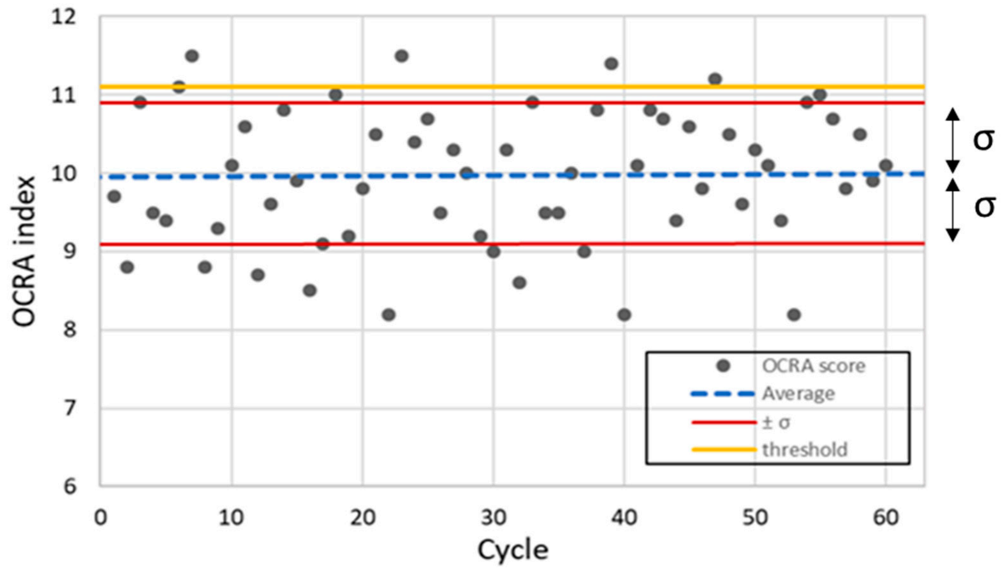

Figure 9. OCRA scores for each working cycle and their statistical values.

The blue dotted line represents the average value of the OCRA score (I_μ), while red lines represent the standard deviation (I_σ) values. Table 4 resumes the statistical values and their comparison with medium risk threshold value (I_t).

Table 4. OCRA score: statistical values.

	Average (I_μ)	Standard Deviation (I_σ)	Medium Risk Threshold Value (I_t)
OCRA index	10.0	0.9	11.0

By applying the Equation (1), it is possible to deduce that, as well as demonstrated by the results in Figure 9, it is verified:

$$I_\sigma = 0.9 < I_t - I_\mu = 1 \tag{7}$$

Thus, as well as for postures, also repetitive actions do not need further investigations, even if in this case the values are borderline between low risk and medium risk areas. This is deducible also from Figure 8, in which more than one cycle has OCRA score within medium risk area.

3.3.2. Critical Issues

Once the results about ergonomics indexes have been obtained, according to the methodological framework in Figure 1, if one or more indexes do not fall within the low risk area, it is appropriate to investigate which sub-phase or specific characteristic of the working cycle mostly contributes to the value of the index.

The analysis of the results related to the case study described shows that the values of exerted forces and the lifting index (NIOSH) exceed the threshold values for the low-risk area; hence, it is necessary an intervention for reducing the injury risk due to biomechanical overload.

Regarding the exerted forces, the value of the counter-reaction force, due to the tightening of the bolt, exceeds the maximum exercisable value. To decrease this force value, it is necessary to use a different type of screwdriver, with a higher lever arm. An angled screwdriver, with a distance between the spindle and the actuation button higher than a gun screwdriver, will significantly reduce the value of the counter-reaction force absorbed by the worker arm.

About the lifting index, according to NIOSH equation, it was deduced that the main contribution to is given by the vertical distance to be covered in handling and the maximum horizontal distance between the handled component and the body, which is excessive especially when the assembly is placed in the cart. In order to reduce the index, it is necessary to think about a reconfiguration of the workstation, lowering the shelf where the components are placed and raising the support surface of the assembly inside the cart.

The next section describes a possible modification of the workstation layout and the type of screwdriver. A simulation will show how this contributes to reduce the value of the risk indexes.

3.4. Proposal and Testing of Improving Solutions

According to the procedure shown in Figure 1, this section aims at proposing workstation layout and equipment changes in order to reduce the values of risk indexes.

As stated in the previous Section 3.3.2, NIOSH lifting index can be reduced by:

- reducing the vertical distance for the operations OP10 and OP20 of Figure 3, so the height of the shelf where the two components are located at the beginning of the working cycle;
- reducing the maximum horizontal distance between the assembly and the body for the operation OP60, which depends on the height of the support surface of the cart, where the assembly is placed.

For this purposes, the shelf has been modified: its height from the ground has been reduced from 1400 mm, as in the previous configuration, 1170 mm. Since the workbench is 900 mm above the ground, the vertical dislocation has been significantly reduced.

The new cart has been designed in order to significantly increase the height of the support surface from the ground: from 500 mm to 1030 mm. In addition, a break has been made to facilitate the positioning of the assembly. In this way the horizontal distance is reduced and the worker does not assume a posture with a large trunk flexion.

Figure 10 shows the new workstation layout.

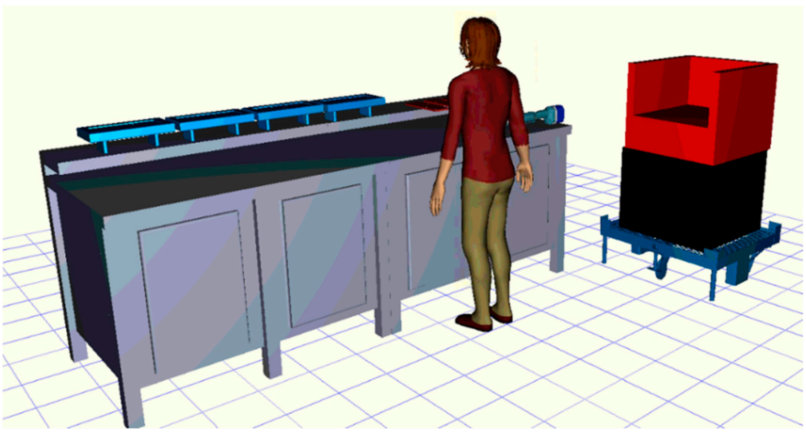

Figure 10. Workstation layout after equipment changes.

Concerning, the counter-reaction force due to the screwing operations, the gun screwdriver has been replaced with an angle screwdriver (Figure 11) with 300 mm lever arm (size "a"), very commonly found on the market.

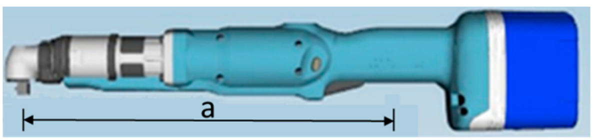

Figure 11. Angle screwdriver; size of lever arm equal to "a".

Figure 12 shows the working tasks after the workstation layout and equipment changes, simulated in Tecnomatix Process Simulate software environment.

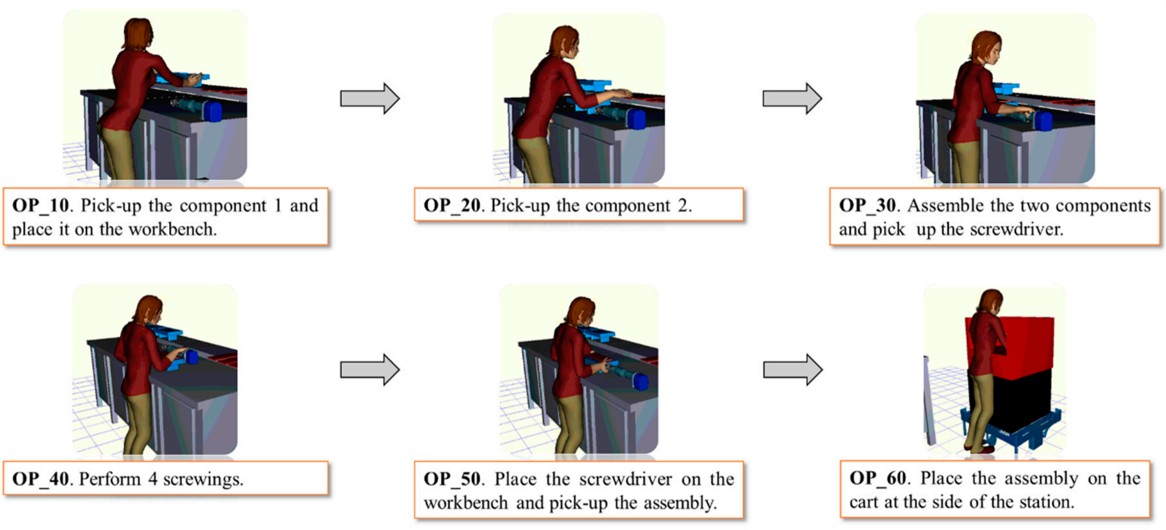

Figure 12. Working tasks after workstation layout and equipment changes.

A simulation has been run in order to numerically evaluate the 4 selected risk indexes. Table 5 shows the risk indexes values related to the new workstation configuration and the comparison with the risk index values evaluated in the previous configuration.

Table 5. Risk indexes comparison after workstation layout changes.

Index	Old Configuration	New Configuration	Reduction [%]
OWAS	146 (±8.3)	118	19.2
Exerted Force	300 N	100 N	66.6
NIOSH	0.96	0.59	38.5
OCRA checklist	10 (±0.9)	10	0

Results show that by modifying the workstation layout and equipment, the risk indexes drastically reduce.

Concerning the critical issues that emerged in the previous analysis, the NIOSH index has been reduced by 38.5% and now it falls within the low risk area. Concerning the exerted forces, despite a reduction of 66%, counter-reaction forces still exceed the upper limit. A further solution could be to change the characteristics of the bolted joints in such a way that a lower tightening torque is required.

However, a reduction in cycle time of about 4 s was also observed. Therefore, considering the unchanged production volume (900 pieces per shift), the recovery time for each cycle would increase. This could balance, at least in part, the biomechanical load due to the exerted forces, which exceed the maximum limit.

Finally, although it already fell within the low risk area, the OWAS index was also reduced by 10%.

4. Discussion

Ergonomic risk mapping of workstations is fundamental, as well as mandatory, for the companies to sustain high efficiency and commercial competitiveness without compromising workers' health and safety. However, the assessment of risk indexes is still carried out by means of observational techniques. This implies that their evaluation becomes high time consuming and, above all, affected by subjective considerations. This research was born with the aim of creating tools that can support experts in ergonomic screening and, above all, can ensure accuracy and repeatability of measurements. From this point of view, the DT can represent the best solution as it allows exploiting the computational capability by using numerical models in which real data, in this case related to human motion, are implemented.

Based on DT, the novel methodological framework here-in proposed has been developed to carefully investigate about ergonomics of manual working tasks in a manufacturing scenario. The case study has been introduced for proving its applicability and effectiveness.

As a consequence, the main implication for ergonomists is related to a significant reduction of the time for evaluating risk indexes, allowing them to focus mostly in identifying issues and proposing solutions. For data collection, we must consider the wearing and calibration time of the wearable system, that typically takes 10-15 min, which is acceptable in comparison to the very short time, in order of seconds, taken by the software for data analysis.

On the other hand, the proposed approach has some limitations, mainly due to the characteristics of software chosen for simulations. The analysis carried out in the present study has been performed by using Tecnomatix Process Simulate, one of the best solutions on the market. However, only some risk assessment methods codes are already implemented in the software (e.g., OCRA index code is not available) and this may require additional effort to implement the algorithm related to a specific index. Moreover, if a re-design of the work station is needed, for example if some issues related to the ergonomic screening tasks occur, the alternative solution is not automatically provided but it needs an analysis by an expert ergonomist. Lastly, in order to obtain a real time analysis, and so a proper DT, the motion capture system must be able to process and transfer data in real time. For the proposed case study, it has been used a system which requires off-line processing.

The literature about the use of human DT for the ergonomic evaluation of workstations is poor as already mentioned in the introduction. However, especially about the application of numerical models for evaluating ergonomic indexes, some comparison considerations can be reported.

First of all, the methodological framework is perfectly in line with the evolution of the topic in the era of industry 4.0, in the use of hardware and software tools for evaluating ergonomic indexes [40].

The present study offers a direct link with experimental data and the use of numerical model with respect to the studies by Caputo et al. [13,14], which are focused on the workstation design validation by considering ergonomic as a design parameter. The advantage offered by this novel methodological framework is the realization of a cyber-physical system in which the motion data of the worker are directly implemented in the simulation model. This offers the possibility to use a numerical model that, on the basis of experimental data, is able to provide ergonomists with a fast and reliable ergonomic screening tool for monitoring the real production.

Similarly, Bortolini et al. [41] carried out a complete ergonomic analysis by setting up an automatic procedure through an optical motion capture system. They used kinematic data for evaluating several risk indexes (OWAS, REBA, EAWS, etc.), demonstrating how such kind of procedures make the ergonomic assessment fast, reliable and objective. The here-in proposed methodology has several advantages compared to [41]. Firstly, the use of a wearable motion capture system allows collecting data directly in a working environment, during the normal production shift, which would be complicated by using optical devices that, although very accurate, are bulky and require a fine calibration. Moreover, the possibility to observe the simulation of the working activity allows immediately identifying possible anomalies and the simulation itself can be used as a training tool for other workers.

An analogous approach has been proposed in Grandi et al. [42], which through virtual environments proposes a workflow for ergonomic assessment during the design with the possibility of using immersive reality devices. However, also this procedure is not completely appropriate as not applicable in a factory environment, where, due to the tight spaces and the high focus that a work task requires, it is not easy to use immersive reality tools.

Zhang et al. [43] proposed a mathematical model for assessing ergonomics and optimizing the assembly line. Although it is a very interesting approach, the model considers only the OCRA index, evaluated according to traditional observational techniques.

The virtual simulation environment described in [17] by using an optical motion capture system is a good tool for the control of working time and quality in a manual manufacturing process. It could benefit from the use of the evaluation ergonomic indexes here proposed to improve the ergonomic performances in the manufacturing production scenario, even though a more performing motion capture device than Microsoft Kinect should be adopted.

The methodology proposed in the present is a contribution towards an innovative way for the ergonomic monitoring of manual workstations and it also contributes at reducing the literature gap about the topic. Collecting experimental data related to real workers, who perform their working tasks during normal working shifts, is extremely fundamental for a correct evaluation, especially in terms of objectivity and repeatability of measurements. In addition, by using cutting-edge technologies, it is possible to perform the ergonomic assessment in real time, with immediate feedback, allowing a significant reduction in evaluation time and, therefore, costs. This approach could be very beneficial for plant ergonomists and occupational physicians.

5. Conclusions

This paper presents a methodological framework, based on Digital Twin, aimed to assess the ergonomic performance in a manufacturing production scenario. Implementing motion data, collected during the working activities, in a virtual 3D scenario allows performing the ergonomic screening of the investigated workstation. In this way it is possible to evaluate the desired risk indexes and figure out eventual production issues.

A case study regarding a simple assembly task has been conducted in a laboratory environment to demonstrate the effectiveness of the proposed framework. Data related to working postures have been collected by a wearable inertial motion tracking system for 60 consecutive working cycles and transferred to the Digital Twin.

In this way it has been possible to easily evaluate four risk indexes related to working postures, exerted forces, material manual handling and repetitive actions, sources of biomechanical overload.

The first simulation figured out issues related to exerted forces and material manual handling, whose values overcame the upper limit of the low risk area. Hence, workstation layout and equipment changes have been proposed and a further time-based simulation has been run to test the solutions. The subsequently ergonomic assessment showed a significant reduction of the risk indexes.

It is fundamental to underline that the traditional ergonomic screenings, carried out in an observational way, are time consuming procedures which require several hours of work. The framework herein proposed allows drastically reducing the evaluation times as well as making the assessment objective and repeatable.

In summary, three important key elements can be pointed out in the present study:

- it has been demonstrated the possibility to assess ergonomics through an automated approach by implementing experimental data, collected by wearable sensors, in a simulation environment, creating the DT of a real manual workstation;
- this approach allows evaluating ergonomics in a faster and more accurate way than manual analysis. In fact, the subjective judgments of analysts are avoided, and the assessment becomes objective based on the used ergonomic indexes;
- the workstations can be continuously monitored, assessing the ergonomic indexes whenever necessary (e.g., in case of change of production volume). Moreover, ergonomists and engineers can identify critical situations, based on real data, and proposing solutions (such as the workstation layout change) to reduce risk indexes. Hence, new solutions may be verified by means of numerical simulation before their implementation.

The procedure described in this paper offers an improvement over current ergonomic screening techniques, but a bigger advantage will come from the use of devices capable of transferring data in real time, providing immediate ergonomic analyses.

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References

1. Alessio, L.; Franco, G.; Tomei, F. *Trattato di Medicina del Lavoro*; Piccin: Padua, Italy, 2015.
2. Bernard, B.; Putz-Anderson, V. *Musculoskeletal Disorders and Workplace Factors; a Critical Review of Epidemiologic Evidence for Work-Related Musculoskeletal Disorders of the Neck, Upper Extremity and Low Back*; NIOSH Publications: Cincinati, OH, USA, 1997.
3. Takala, E.P.; Pehkonen, I.; Forsman, M.; Hansson, G.A.; Mathiassen, S.E.; Neuman, W.P.; Sjøgaard, G.; Veiersted, K.B.; Westgaard, R.H.; Winkel, J. Systematic Evaluation of Observational Methods Assessing Biomechanical Exposures at Work. *Scand. J. Work Environ. Health* **2010**, *36*, 3–24. [CrossRef]
4. Fera, M.; Greco, A.; Caterino, M.; Gerbino, S.; Caputo, F.; Macchiaroli, R.; D'Amato, E. Towards Digital Twin Implementation for Assessing Production Line Performance and Balancing. *Sensors* **2020**, *20*, 97. [CrossRef]
5. Cao, X.; Cheng, P.; Chen, J.; Sun, Y. An Online Optimization Approach for Control. *IEEE Trans. Ind. Inform.* **2013**, *9*, 439–450. [CrossRef]
6. Kadir, B.A.; Broberg, O.; da Conceição, C.S. Current research and future perspectives on human factors and ergonomics in Industry 4.0. *Comput. Ind. Eng.* **2019**, *137*, 106004. [CrossRef]
7. Atzori, L.; Iera, A.; Morabito, G. The Internet of Things: A survey. *Comput. Netw.* **2010**, *54*, 2787–2805. [CrossRef]
8. Kuruganti, U. 22—Sensors for Monitoring Workplace Health. In *Bioelectronics and Medical Devices*; Woodhead Publishing Series in Electronic and Optical Materials; Woodhead Publishing: Cambridge, UK, 2019; pp. 537–553.
9. Lim, S.; D'Souza, C. A narrative review on contemporary and emerging uses of inertial sensing in occupational ergonomics. *Int. J. Ind. Ergon.* **2020**, *76*, 102937. [CrossRef]
10. Hajifar, S.; Sun, H.; Megahed, F.M.; Jones-Farmer, L.A.; Rashedi, E.; Cavuoto, L.A. A forecasting framework for predicting perceived fatigue: Using time series methods to forecast ratings of perceived exertion with features from wearable sensors. *Appl. Ergon.* **2021**, *90*, 103262. [CrossRef]
11. Banks, J.; Carson, J.S., II; Nelson, B.L.; Nicol, D.M. *Discrete-Event System Simulation*, 5th ed.; Essex: Harlow, UK, 2019.
12. Alkan, B.; Vera, D.; Ahmad, M.; Ahmad, B.; Harrison, R. A model for complexity assessment in manual assembly operations through predetermined motion time systems. *Proc. CIRP* **2016**, *44*, 429–434. [CrossRef]
13. Caputo, F.; Greco, A.; Fera, M.; Macchiaroli, R. Digital twin to enhance the integration of ergonomics in the workplace design. *Int. J. Ind. Ergon.* **2019**, *71*, 20–31. [CrossRef]
14. Caputo, F.; Greco, A.; Fera, M.; Macchiaroli, R. Workplace design ergonomic validation based on multiple human factors assessment methods and simulation. *Prod. Manuf. Res.* **2019**, *7*, 195–222. [CrossRef]
15. Makarova, I.; Khabibullin, R.; Belyaev, E.; Mavrin, V.; Verkin, E. Creating a safe workin environment via analyzing the ergonomic parameters of workplaces on an assembly conveyor. In Proceedings of the 2015 International Conference on Industrial Engineering and Systems Management (IESM), Seville, Spain, 21–23 October 2015. [CrossRef]

16. Case, K.; Hussain, A.; Marshall, R.; Summerskill, S.; Gyi, D. Digital human modelling and the ageing workforce. *Procedia Manuf.* **2015**, *10*, 3694–3701. [CrossRef]
17. Tarallo, A.; Mozzillo, R.; Di Gironimo, G.; De Amicis, R. A cyber-physical system for production monitoring of manual manufacturing processes. *Int. J. Interact. Des. Manuf.* **2018**, *12*, 1235–1241. [CrossRef]
18. Sanjog, J.; Patel, T.; Karmakar, S. Occupational ergonomics research and applied contextual design implementation for an industrial shop-floor workstation. *Int. J. Ind. Ergon.* **2018**, *72*, 188–198. [CrossRef]
19. Catarci, T.; Firmani, D.; Leotta, F.; Mandreoli, F.; Mercella, M.; Sapio, F. A conceptual architecture and model for smart manufacturing relying on service-based digital twin. In Proceedings of the 2019 IEEE International Conference on Web Services (ICWS), Milan, Italy, 8–13 July 2019.
20. Malik, A.A.; Bilberg, A. Digital twins of human robot collaboration in a production setting. *Procedia Manuf.* **2018**, *17*, 278–285. [CrossRef]
21. Li, C.; Fahmy, A.; Sienz, J. An augmented reality based human-robot interaction interface using Kalman filter sensor fusion. *Sensors* **2019**, *19*, 4586. [CrossRef]
22. Nikolakis, N.; Alexopoulos, K.; Xanthakis, E.; Chryssolouris, G. The digital twin implementation for linking the virtual representation of human-based production tasks to their physical counterpart in the factory floor. *Int. J. Comput. Integr. Manuf.* **2019**, *31*, 1–12. [CrossRef]
23. Zheng, Y.; Yang, S.; Cheng, H. An application framework of digital twin and its case study. *J. Ambient Intell. Humaniz. Comput.* **2019**, *10*, 1141–1153. [CrossRef]
24. Ma, J.; Chen, H.; Zhang, Y.; Guo, H.; Ren, Y.; Mo, R.; Liu, L. A digital twin-driven production management system for production workshop. *Int. J. Adv. Manuf. Technol.* **2020**, *110*, 1385–1397. [CrossRef]
25. Kunath, M.; Winkler, H. Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process. *Procedia CIRP* **2018**, *72*, 225–231. [CrossRef]
26. Harvard, V.; Jeanne, B.; Lacomblez, M.; Baudry, D. Digital twin and virtual reality: A co-simulation environment for design and assessment of industrial workstation. *Prod. Manuf. Res.* **2019**, *7*, 472–489.
27. Caputo, F.; Greco, A.; D'Amato, E.; Notaro, I.; Lo Sardo, M.; Ghibaudo, L. A Human Posture Inertial Tracking System for Ergonomic Assessment. *Adv. Intell. Syst.* **2019**, *825*, 173–184.
28. Giacomazzi, F.; Conti, C. *Manuale di Gestione Della Produzione*, 3rd ed.; ISEDI: Milano, Italy, 1975.
29. Tecnomatix. Available online: https://www.plm.automation.siemens.com/global/en/products/tecnomatix/ (accessed on 28 July 2020).
30. Delmia. Available online: https://www.3ds.com/products-services/delmia/ (accessed on 28 July 2020).
31. *ISO 11226: Ergonomics—Evaluation of Static Working Postures*; ISO: Geneva, Switzerland, 2000.
32. *ISO 11228-1: Ergonomics—Manual Handling—Part 1: Lifting and Carrying*; ISO: Geneva, Switzerland, 2006.
33. *ISO 11228-2: Ergonomics—Manual Handling—Part 2: Pushing and Pulling*; ISO: Geneva, Switzerland, 2006.
34. *ISO 11228-3: Ergonomics—Manual Handling—Part 3: Handling of Low Loads at High Frequency*; ISO: Geneva, Switzerland, 2007.
35. Snook, S.H.; Ciriello, V.M. The design of manual handling tasks: Revised tables of maximum acceptable weight and forces. *Ergonomics* **1991**, *34*, 1197–1213. [CrossRef]
36. Masali, M. *L'Italia si Misura. Vademecum Antropometrico per il Design e L'ergonomia. Vent'anni di Ricerche (1990–2010)*; Aracne Editore: Rome, Italy, 2015.
37. Louhevaara, V.; Suurnäkki, T.; Hinkkanen, S.; Helminen, P. *OWAS: A Method for the Evaluation of Postural Load during Work*; Institute of Occupational Health, Centre for Occupational Safety: Helsinki, Finland, 1992.
38. Waters, T.R.; Putz-Anderson, V.; Garg, A. *Applications Manual for the Revised NIOSH Lifting Equation*; National Institute for Occupational Safety and Health: Washington, DC, USA, 1994.
39. Colombini, D.; Occhipinti, E.; Alverez-Casado, E. *The Revised OCRA Checklist Method*; Editorial Factor Humans: Barcelona, Spain, 2013.
40. Mgbemena, C.E.; Tiwari, A.; Xu, Y.; Prabhu, V.; Hutabarat, W. Ergonomic evaluation on the manufacturing shop floor: A review of hardware and software technologies. *CIRP J. Manuf. Sci. Technol.* **2020**, *30*, 68–78. [CrossRef]
41. Bortolini, M.; Gamberi, M.; Pilati, F.; Regattieri, A. Automatic assessment of ergonomic risk for manual manufacturing and assembly activities through optical motion capture technology. *Proc. CIRP* **2018**, *72*, 81–86. [CrossRef]

42. Grandi, F.; Peruzzini, M.; Zanni, L.; Pellicciari, M. An automatic procedure based on virtual ergonomic analysis to promote human-centric manufacturing. *Proc. Manuf.* **2019**, *38*, 488–496.
43. Zhang, Z.; Tang, Q.H.; Ruiz, R.; Zhang, L. Ergonomic risk and cycle time minimization for the U-shaped worker assignment assembly line balancing problem: A multi-objective approach. *Comput. Oper. Res.* **2020**, *118*, 104905. [CrossRef]