International Journal of the Digital Human

ISSN online: 2046-3383 - ISSN print: 2046-3375
https://www.inderscience.com/ijdh

Verification of manikin motions in human-industrial robot collaborative simulations

Fredrik Ore, Pamela Ruiz Castro, Lars Hanson, Magnus Wiktorsson, Stefan Gustafsson

DOI: 10.1504/IJDH.2022.10049475

Article History:

Received:	28 February 2019
Accepted:	05 July 2021
Published online:	25 August 2023

Verification of manikin motions in human-industrial robot collaborative simulations

Fredrik Ore*

School of Innovation, Design and Engineering,
Mälardalen University,
Eskilstuna, Sweden
and
Scania CV AB,
Global Industrial Development,
Södertälje, Sweden
Email: Fredrik.ore@scania.com
*Corresponding author

Pamela Ruiz Castro

School of Engineering Science,
University of Skövde,
Skövde, Sweden
Email: Pam.r.castro@gmail.com

Lars Hanson

School of Engineering Science,
University of Skövde,
Skövde, Sweden
and
Department of Industrial and Materials Science,
Chalmers University of Technology,
Gothenburg, Sweden
Email: lars.hanson@scania.com

Magnus Wiktorsson

School of Innovation, Design and Engineering,
Mälardalen University,
Eskilstuna, Sweden
and
KTH, School of Industrial Engineering and Management,
Södertälje, Sweden
Email: magwik@kth.se

Stefan Gustafsson

Industrial Path Solutions Sweden AB,
Chalmers Teknikpark, 412 88 Göteborg
Email: stefan.gustafsson@industrialpathsolutions.se

Abstract: A recently developed simulation software, IPS-HIRC, combines digital humans and industrial robots into one environment in order to design human-industrial robot collaborative (HIRC) workstations. The aim of this study is to verify the manikin motions predicted by the mathematical algorithm in the software with results obtained from motions performed by humans in experiments. These motions are measured through motion capture data on humans performing a HIRC work task in laboratory workstations. These stations represent HIRC workstations considered in an international heavy vehicle manufacturing company. The results showcase significant correlations in the motions in one of the two use cases, but fewer correlations when comparing the total operation time. The main reason for this is the complexity of the two cases and the lack of professional assembly experience among the test participants. Thus, new verification studies are needed in use cases that more properly represent human motions in a manufacturing workstation.

Keywords: human-robot collaboration; HRC; simulation; verification; validation; digital human modelling; DHM; industrial robot; motion capture; workstation.

Reference to this paper should be made as follows: Ore, F., Castro, P.R., Hanson, L., Wiktorsson, M. and Gustafsson, S. (2023) 'Verification of manikin motions in human-industrial robot collaborative simulations', *Int. J. Digital Human*, Vol. 2, No. 3, pp.160–178.

Biographical notes: Fredrik Ore is an Industrial PhD student in the research area of Innovation and Product Realisation at Mälardalen University in Eskilstuna, Sweden. His research is in the field of simulation, evaluation and optimisation of human-industrial robot collaboration. He has a Master of Science in Mechanical Engineering from Luleå University of Technology and has been a doctoral student at the Innofacture Research School at Mälardalen University since late 2012. Before his PhD studies, he had eight years of practical industrial experience from various manufacturing employments.

Pamela Ruiz Castro is a research assistant for the User Centred Product Design research group from university of Skövde. She has a BSc in Product Design Engineering from university of Skövde. She works with virtual ergonomics and supports various studies in the area of manufacturing ergonomics. Her interests include human-robot collaboration as well as application of technology resources that aid in the study or ergonomics.

Lars Hanson is a Professor of Product and Production Development at the School of Engineering Science, Skövde University. His research interest is human machine interaction with special focus on digital human modelling. Hanson is also managing the activities at Scanias Smart Factory Lab, a lab there technologies and processes are adapted, evaluated and demonstrated.

Magnus Wiktorsson is a Professor of Production Logistics at the Department for Sustainable Production Develoment, at KTH – Royal Institute of Technology. He is also a Visiting Professor at Mälardalen University. His research interest concerns how complex production and logistic systems can be described and predicted, especially considering industrial digitisation and sustainability.

Stefan Gustafsson is a software developer at Industrial Path Solutions. He has a BSc in Mathematics from Gothenburg University. He works on the IPS software as developer and overall release manager, recently focussing his development efforts on adding virtual reality support to the program. His interests include large-scale software development and the C++ programming language, as well as computer graphics.

1 Introduction

Human-industrial robot collaboration (HIRC) aims to combine positive characteristics of humans and industrial robots in an industrial environment. These systems are developed with the aim to combine robotic strength, endurance and accuracy with human flexibility, intelligence and tactile sense (Krüger et al., 2005; Stopp et al., 2002). In order to reach this aim, collaborative operations between fenceless industrial robots and humans are proposed in research. This field has increased rapidly in the last decade (Ore, 2015; Tsarouchi et al., 2016) and personal safety for the operators has been the main prerequisite for HIRC workstation design (Michalos et al., 2015). A few examples of collaborative applications have been installed in industries in recent years (Bauer et al., 2016).

Appropriate design is another challenging task of HIRC workstation implementation. Such a design should consider productivity goals as well as work environment demands on the human. In other areas than HIRC, such as simulation of material flow, layout planning, supply chain, digital human modelling (dhm) and robotics, decisions are often made with the help of manufacturing simulation software (Mourtzis et al., 2015). Such tools are used to make production design decisions in early phases of the production development process. The reason for the popularity of simulation software is that it enables manufacturing engineers and decision makers to analyse and evaluate how changes in complex manufacturing systems affect their overall performance (Baldwin et al., 2000). However, simulation of HIRC workstations is limited in software and research. Recently a demonstrator software has been developed to fill this gap (Ore et al., 2015). This HIRC simulation software enables visualisation and evaluation of hand-guiding HIRC tasks in 3D environments. The software can be used to analyse reachability for both robots and humans, present technical solutions and be an input to risk assessment in HIRC workstation design tasks. It also outputs quantitative numbers considering operation time and biomechanical load assessments. The HIRC software is based on the DHM software IPS IMMA, where the human is represented by a virtual manikin consisting of a skeleton of links connected by joints creating a system with 162 degrees of freedom (IPS, 2019b). The virtual manikins use inverse kinematics and mathematical algorithms to normalise the loads on each joint in order to determine a posture with the most favourable biomechanical load (Bohlin et al., 2012). Adding theses postures together creates a motion. This research software is named IPS-HIRC in this paper. The software developers have clarified that the objective is not to claim that the motion prediction function is to produce an exact motion performed by a certain human but to confirm that it is possible to accomplish the task in the virtual environment (Högberg et al., 2016). And if no ergonomically acceptable motion can be found, action must be taken (Bohlin et al., 2012). However, it is of interest to investigate the fidelity of the simulation results, in order to build reliability in the simulation software. Fidelity is defined in the US Department of Defense Modeling and Simulation Enterprise glossary as the degree to which a simulation represents the behaviour of a real-work object (The Department of Defense Modeling and Simulation Enterprise, 2021).

As these simulated manikin motions have not yet been experimentally verified, the aim of this study is to verify the biomechanical load and operation time predicted by the IPS-HIRC research software with results obtained from motions performed by humans. This paper investigates two hypotheses connected with the fidelity of the simulation software, first that the biomechanical load in the simulation results is verified by physical experiments, and second that operation time results from the software are verified by physical experiments.

2 Method

In order to verify the simulated motions, two physical demonstrators of HIRC workstations were used. Both are physical mock-ups of existing manual workstations at an international heavy vehicle manufacturing company. Case A is from a machining environment, at the inspection of an engine block, and case B is from an assembly plant, the flywheel cover assembly on an engine. These stations are described below together with an explanation of the process of collecting motion data from both simulated and physical human motions.

2.1 Physical demonstration stations

Cases A and B were of interest to the manufacturing company as industrial robots might assist in reducing ergonomic load on human operators and improve the productivity of the systems in both cases. Physical mock-ups were built with dual purposes, to demonstrate future possibilities of HIRC workstations and to be used in the verification of the simulated motions in this study.

2.1.1 Engine block inspection – Case A

This workstation is located at the end of the machining process, where manual inspection of the engine block surfaces is conducted. The current process includes a manually controlled rotating device that indexes the engine block to predefined positions that enable visual inspection to find any flaws on the engine block. The inspection is carried out manually with a flashlight. This process involves awkward biomechanical positions and time constraints on the operators [Figure 1(a)]. Thus a HIRC system has been proposed as a suggested future workstation [Figure 1(b)] (Khalid et al., 2015). This new system includes a large industrial robot handling the heavy (ca. 300 kg) engine block and presenting it to the human operators at suitable positions.

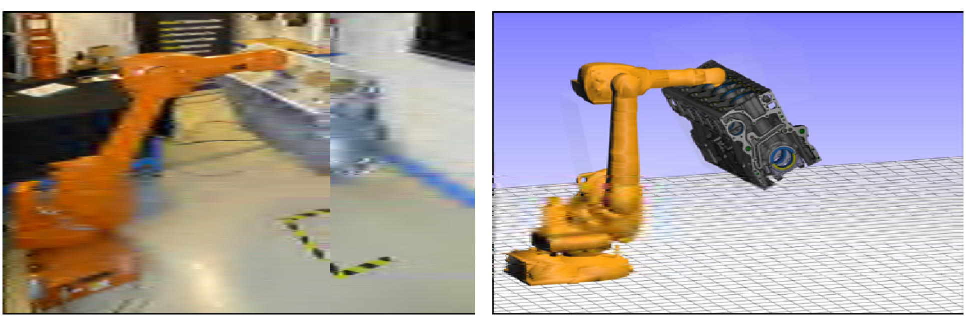
A physical prototype of the engine block inspection station was created. The largest available robot was the ABB robot (ABB IRB 1600/1.45) with a payload of 10 kg, and it was used in the experiment. The prototype cell was used to inspect the same surfaces as those treated in the existing manufacturing station. To enable this, a lightweight prototype with the same outer dimensions as a real engine block had to be created. A styrofoam replica with a weight of 3.9 kg was produced. The replica had the correct outer dimensions in a partly simplified rectangular cuboid shape. Photographs of the engine block were attached on the surface of the model in order to make it look more realistic, as the task was to inspect the surface to find cracks. The prototype station with the robot and the engine block replica is shown in Figure 2(a) and the virtual copy of the lab environment created in the HIRC simulation software in Figure 2(b).

Figure 1 (a) Bad biomechanical posture in existing inspection of engine block, (b) proposed HIRC solution (see online version for colours)

(a) (b)

Source: Khalid et al. (2015)

Figure 2 Engine block inspection workstation used in verification, (a) physical station (b) virtual model (see online version for colours)

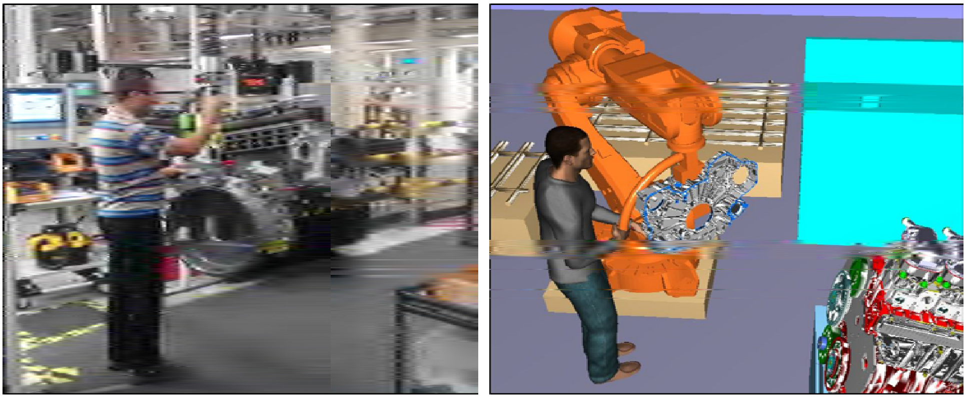


(a) (b)

2.1.2 Flywheel cover assembly – Case B

The assembly of flywheel covers is done in the engine assembly plant. The flywheel cover is an aluminium object with a weight of 15 kg and a diameter of 0.6 meters that is assembled on the short side of the engine block. It is currently handled in the assembly station by a pneumatic lifting tool and an overhead rail system controlled by manual force from the operator [Figure 3(a)]. In order to meet new products in the station with reduced assembly time, a HIRC system was proposed where the robot manoeuvres the flywheel cover in the station while the human hand guides it to its final assembly position, [Figure 3(b)] (Ore et al., 2016).

Figure 3 (a) Handling of flywheel cover at the existing engine assembly plant, (b) proposed HIRC solution (see online version for colours)



(a) (b)

Source: Ore et al. 92016)

A physical demonstrator was created in a lab environment. The focus was the actual hand-guiding part of the station, including automatic motion of robot to human handover, the hand-guided handling of the flywheel cover to the assembly position, the return of the empty robot gripper and finally the start of automated robotic motion. Figure 4(a) presents this prototype station with the flywheel cover at the handover position and Figure 4(b) the virtual copy used in the verification.

Figure 4 Flywheel cover assembly workstation used in verification, (a) physical station (b) virtual model (see online version for colours)

(a) (b)

2.2 *Physical experiment*

In both prototype stations the human motion data were collected through the Xsens motion capture system MVN Awinda and analysed with the corresponding software MVN Studio 4.3 (Xsens, 2019). The process is described below.

Voluntary test subjects performed the HIRC work cycles. In Case A, a total of 13 participants performed the task and in case B 12. Table 1 presents the characteristics of the participants. In Case B four of the 12 persons were skilled assembly employees from the same engine assembly factory where the current flywheel cover assembly in Case B is done. The other test subjects were all recruited from the authors' student network and had limited practical manufacturing experience.

Table 1 Characteristics of test participants and virtual manikins for Cases A and B

	Sex (n)		*Stature (cm)*			*Avg. age*
	Male	*Female*	*Min*	*Average*	*Max*	
Test persons Case A	9	4	160	171	195	32.6
Test persons Case B	10	2	162	177	191	33.3
Virtual manikins Cases A & B	5	5	153	173	194	NA

The motion tracker system consists of 17 wireless motion trackers (sensors) placed at predefined locations on the body and secured with straps. The motion trackers are small measurement units (34.5 x 57.8 x 14.5 mm) containing 3D linear accelerometers, 3D rate gyroscopes, 3D magnetometers and a barometer. Each sensor contains a rechargeable internal battery. Figure 5 shows the placement of the motion trackers on the human body.

Figure 5 Placement of motion trackers on human body (see online version for colours)

The motion trackers collect raw sensor data with a sample rate of 60 Hz that are filtered and then projected on a biomechanical human model available through the corresponding Xsens MVN Studio 4.3 software.

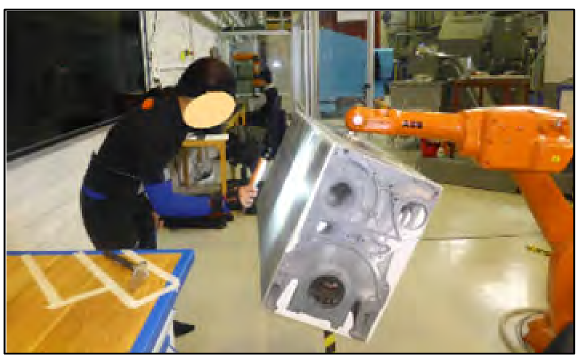
Before running any test, the aim of the study and the process of the test were described to each test participant. Eight body dimensions were also measured in order to create the digital human model needed to transform the sensor data to the physical characteristics. They were body height, foot size, arm span, ankle height, hip height, hip width, knee height, shoulder width and shoe sole height (Schepers et al., 2018). The participants were then equipped with the sensors followed by one practice test of the work task cycle in order for them to become familiar with the assignment. The motion trackers were then calibrated before the recordings began (Schepers et al., 2018).

The operators performed their work task in two (Case B) or three (Case A) full work cycles. The data were collected in real time through the motion tracker system, and the resulting joint angles from the motion of the test subjects' last work cycle together with the time to complete the tasks were extracted in order to be analysed at a later stage.

2.2.1 Test cycle engine block inspection – Case A

The test cycle task comprised visual inspection of five sides of the engine block, which are easy to access, with a flashlight. In an industrial setting the sixth surface (on the top) of the engine block must be inspected before the robot lifts the block. The subjects stood at a marked spot outside the robot motion area at the start and end of the work task and also during robot motion, when the robot indexed the engine block to present different sides to the operator. The subjects held the flashlight in their right hand and checked the surfaces for fractures (Figure 6). Small holes (3–8 mm in diameter) had been drilled on the surface of each side of the engine block replica and the test subjects were asked to count these in order to engage the participants in the inspection process. The number of identified holes was given after each side had been inspected.

Figure 6 Test subject inspecting the engine block (see online version for colours)



2.2.2 Test cycle flywheel cover assembly – Case B

This assembly task test cycle included the hand-guided handling of the flywheel cover from the handover position to the final assembly position, placing the flywheel cover on the engine block and hand-guiding the robot (without an object) back to the handover position. A position outside the collaborative work area was designated as the start and end position of the operators.

The robot end effector was a combination of a gripper and an enabling device. A force-torque sensor was used to transfer the human intentions to robotic motions through manual forces on the handles. The hand-guiding was controlled through two enabling devices, one in each hand. Engaging them while pushing in the intended motion direction triggered robot and flywheel cover motion. To enable the assembly of the flywheel cover on the existing guiding pins on the engine block, the motions of the operator were limited to only allow translations in the horizontal plane. This station is described in Gopinath et al. (2018). Figure 7 shows a test participant performing the assembly.

Figure 7 Test subject assembling flywheel cover (see online version for colours)

2.3 Collecting motion capture data from physical experiment

Joint angles of the digital human model from the Xsens system were collected during the work tasks. Data from the last performed motion were used for the analysis. The system extracted 22 joint data from the human motions all divided into X, Y and Z rotations summing up 66 measurement values that represent the human motions. Operation times for performing the complete work cycles were also extracted from the motion capture system.

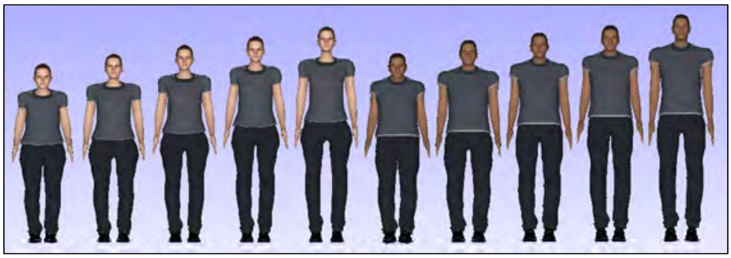
During the data capture, problems with the wireless sensors were experienced due to electromagnetic disturbances in the physical test environment. Consequently, a number of collected data could not be used for verification. In Case A seven and in Case B ten of the participants' data could be used for further analysis.

2.4 Simulated experiment

The simulation was performed on a research version of the IPS simulation software (IPS, 2019a). This is referred to as IPS-HIRC simulation software in this paper and the simulation process described by Ore et al. (2015) was used to create the virtual simulation of both cases. The IPS-HIRC simulation software is a combination of the digital human modelling (Högberg et al., 2016) and robotic parts (Spensieri et al., 2013) of the IPS software. Numerical evaluation of the performance of a HIRC system is possible through the software. It evaluates total operational time as well as the biomechanical load on the operator. Robotic operation time is calculated through the robotic optimisation techniques in the software. Human times are analysed through the methods-time measurement (MTM) method (Maynard et al., 1948) in the software. Biomechanical load is measured through the rapid upper limb assessment (RULA) method (McAtamney and Corlett, 1993). RULA investigates the musculoskeletal injury risk on humans by evaluating the individual poses and assessing the injury risks of these on the human body. A human movement is divided into a number of poses and in each of these the joint values of the manikin are analysed with RULA. RULA analyses both right and left arm, and the worst value is used for further analysis. The result from a RULA analysis is a grand score that represents a musculoskeletal risk level from one to seven. A high score (between five and seven) indicates a high risk of injury on the operator. Finally a time-averaged RULA score is calculated that combines the time measurements as it also considers the time spent on each RULA level (Vignais et al., 2017).

To be able to imitate the human variation in anthropometrics of physical test persons, a family of manikins was used. An average family was created in the software consisting of ten manikins, five males and five females. The manikins were created with weight and stature as key measurement parameters, with a 95% confidence interval for each sex (Bertilsson et al., 2011). Swedish anthropometric data presented by Hanson et al. (2009) were used for the manikin creation. Figure 8 visually represents the family; the stature of the manikins is presented in Table 1.

Figure 8 Manikin family used in both simulated cases (see online version for colours)



Geometrical copies of the physical stations were created in a CAD software and imported into the HIRC simulation software. The simulation sequence was then created through a high-level language introduced in the software (Mårdberg et al., 2014). This language enables instruction of the manikin through commands such as *grasp*, *move to*, *look at* and *follow*. The positions to *grasp*, *move to* and *look at* have to be defined in the virtual environment, but the software automatically calculates a motion to perform the activity. *Follow* is the function where the manikin carries an object through a predefined collision-free path. The resulting joint angles from the motions of the manikins were extracted in order to be analysed at a later stage. Time of the simulated motions was also extracted from the software.

2.5 Collecting motion capture data from simulation

The joint angles from the software consist of 134 data values for translation and rotation of joints representing the human body. A digital human motion consists of a number of postures from each frame in the simulation; the sampling rate is dependent on the motion of the manikin and its interactions with surrounding objects, but the frequency goes down to 1,000 Hz as lowest, with 140 Hz as median. In the analysis a time-weighted factor considering the duration of the posture is used to compensate for these variations.

2.6 Analysing joint values from simulation and physical tests

The output from the biomechanical model from the IPS-HIRC software is joint angles for each of the joint segments creating the skeleton (in total 134 values), similar to the Xsens Awinda system, only with fewer data points (66 values). Since the RULA analysis had already been implemented in the IPS-HIRC software, the same function was also included to analyse the physical motions and the data were then used in the evaluation of motion data.

The RULA evaluation for both the physical and the virtual experiments is analysed numerically through joint data evaluation. A time-averaged RULA value that considers duration of the individual frames was calculated to be used in the following analysis. The

RULA employee assessment worksheet presented by McAtamney and Corlett (1993) puts discrete limits to the assessing of joint angles. These limits are slightly adapted to suit virtual simulations, as the threshold between certain postures gives a very high impact on the final result. An example is neck position in extension in the RULA employee assessment worksheet giving a high penalty. However, the software can generate small numbers (e.g. 0.03°) and interpret that as a backward motion of the head, while the practical value of this angle is a neutral neck position. Thus the limit to identify a negative extension in the neck is interpreted to be >2°. The full adaptation of the RULA employee assessment worksheet to numbers used in the virtual evaluation is presented in Appendix A.

3 Results

The RULA and time values used for the verification analysis are presented in Table 2 and the boxplots of these data are presented in Figure 9.

Table 2 Values of RULA and time in simulated and physical experiments

	CASE A – ENGINE BLOCK INSPECTION			
	Simulated (n = 10)		*Physical (n = 7)*	
	RULA	*time (s)*	*RULA*	*time (s)*
min	4.39	59.86	3.36	59.44
average	4.96	62.28	5.23	84.10
max	5.29	63.94	5.90	93.67
	CASE B – FLYWHEEL COVER ASSEMBLY			
	Simulated (n = 10)		*Physical (n = 10)*	
	RULA	*time (s)*	*RULA*	*time (s)*
min	3.09	22.22	3.21	60.44
average	3.10	22.61	3.51	108.02
max	3.12	23.03	4.16	150.76

Since the test samples are few and normal distributions cannot be assumed (the RULA values are limited to be integers from 1 to 7), a Mann-Whitney U test was used to do the statistical evaluation (Marusteri and Bacarea, 2010; Nachar, 2008). 5% was chosen as the significant level and the resulting p-values are presented in Table 3. Neither of the hypotheses are true in both cases. The hypothesis that the biomechanical load in the simulation results are verified by physical experiments is true for case A, but not for B, and the same result is valid for the operation time hypothesis. It is true for A but not for B.

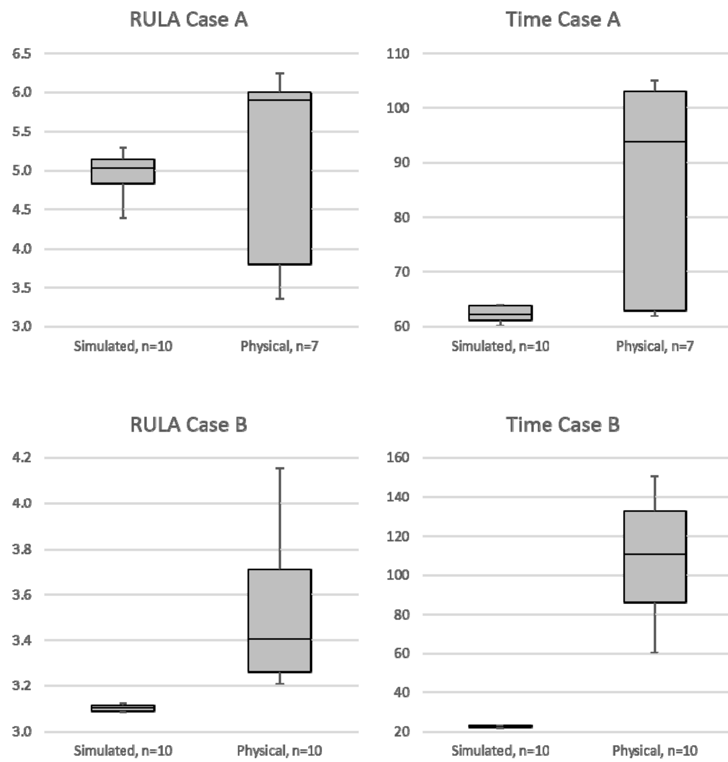
Table A3 P-values comparing RULA and time of the two cases investigated

	Case A – RULA	*Case A – time*	*Case B – RULA*	*Case B – time*
P-value	0.143	0.079	0.0002	0.0002

4 Discussion

The results presented above show no significant difference in Case A and significant difference in Case B between the motions simulated through the IPS-HIRC software and the physical ones. These results are discussed in detail below, focusing on the individual results as well as on the method.

Figure 9 Boxplots of RULA and time values from simulated and physical experiments (see online version for colours)



4.1 Results discussion

The boxplots in Figure 9 show that the variation of physical human motions is much larger than that in simulation. The main reason for this is the deterministic nature of the prediction of human motions in the simulation software that one task is always performed in the same way by one manikin. When a manikin family is introduced in the software, all the family manikins perform the task in the same way with the same *grasp*, *move to* and *look at* positions and follow the same paths, however with adjustments on the manikin motions due to different anthropometrics. This deterministic feature results in consistent simulation results irrespective of which simulation engineer performs the simulation, and this objectivity with respect to software user is considered a benefit (Högberg et al., 2016). However, in practice there is always a variation in human motions if one human performs the same task multiple times and even higher variance when multiple physical test persons perform the same task. These human variations are limited by the instructions of the task (where to move, what to do there, and so on), but the freedom within these constraints adds variation between individual humans performing a task (Zhang and Chaffin, 2005). However, none of this is included in the software.

There are also current limitations in the software that decreases the accuracy in simulating physical human motions. For instance, the path that the digital manikin is asked to follow between *grasp* and *release* positions is calculated before the manikin actually performs it. This enables faster simulation since biomechanical constraints are not needed to be considered, as the collision-free path is defined. However, this might result in paths that do not necessarily bring about the most biomechanically friendly motion available (a simple example is that the extremely tall and short manikins follow the same path from position A to B). This could be improved if only the start and end positions were set as constraints, thus allowing the software to calculate the best way between these positions. This would most likely enable more accurate simulation of physical human motions, with the cost of more time-consuming simulations. A hybrid to allow fast computing and reliable motion results is under development, a function by which the manikin can relax from the pre-planned path to obtain more biomechanically friendly motions.

4.1.1 Case A

Based on the p-values calculated on the RULA and time measurements in Case A, the results show that the simulated motions can be said to mimic the physical ones.

There is, however, a huge variation in the measured physical data. Besides the general software-dependent reason described above, the main reason for this was the visual inspection that is the main part of the task in Case A. There was no exact biomechanical posture present on how to make the visual inspection, and two groups of test participants emerged. One group (two test participants) was quite relaxed, inspected with a straight back and preferred a better biomechanical position to one closer to the engine block. The second group held an awkward position with greater back-bending to get their eyes closer to the engine. The simulation software selected an inspection strategy resulting in a RULA score somewhere in between the two groups.

The same discussion is valid considering the time duration of the inspection. Also in this case two groups emerged from the data. One group with three test participants finalised the task in 62.0s, close to the average of the simulated manikins (62.3s). The other group ($n = 4$) had an average of 100.7 s. The main reason for the large variety in the duration of the task is the time needed for visual inspection. In the simulation software, the predetermined motion functionality reading in SAM was used. SAM is based on the MTM method and collects a number of MTM motions in larger groups enabling more efficient analysis (Laring et al., 2002). The reading term in SAM defines the time it takes to visually inspect a certain area (Hasselqvist et al., 1969). The differences in inspection time could not be related to bad inspection quality in this task since the number of identified holes on the fictive engine block has no correlation with the inspection time.

4.1.2 Case B

Case B showed worse verification results. Neither the p-values for RULA nor the time indicated any connection between the simulated and the physical values.

The average values of the RULA results show relatively small differences between the simulated and the experimental data. However, the extremely small variance of the simulation results in no correlations between the datasets. The main reason for the small differences in the simulated motions is that a great part of the work task includes holding the enabling device and moving the robot through manual motions (as can be seen in Figure 7). When this task is designed in the simulation software, the constraints are set and hold through the whole motion, resulting in steady values irrespective of small differences in stature. While the manikin is set to look at the final assembly position, the human does things slightly differently and looks at different positions (the object, the final assembly position, the floor, the surrounding). The human also tends to move the flywheel cover in different ways (some tend to push it, while others pull it). A closer investigation of the data from the four skilled assembly employees from the same engine assembly factory shows a better match with the simulated results (an average of 3.42, compared to 3.58 for the other six participants). This indicates the importance of performing measurements on experienced assembly operators to get more reliable results. However, access to such operators is limited in these kinds of tests. None of the physical demonstration stations was built in the same city where the manufacturing industry has its production facilities, and the possibility for operators to leave production during a full day is extremely limited. This should, however, be considered in future verification studies.

Case B shows an extremely large difference in operation time between physical and simulated tests (3–7 times longer in physical tests). This originates mainly from the difficulty for all the physical test persons to manipulate the hand-guiding enabling device for the robot. The two three-positioned enabling devices (one in each hand) were difficult to activate correctly; if one or the other was pushed too hard or too softly, the robot motion was stopped. The large variation among the test participants also shows the great difference in how difficult different persons found this task to be. This fumbling will decrease if operators are trained to perform the task; it is, however, impossible to say whether the simulated time is representative of what an experienced operator would take to perform it.

4.2 Method discussion

The collected data from the physical tests in Case A showed irregular values in a number of tests. The real-time visualisation in the Xsens software showed that the spine of the visual manikin was unnaturally twisted. This motion, which did not correspond to the actual movements of the test participants, only occurred occasionally. The problem originated from electromagnetic fields in the lab. Due to these electromagnetic interferences, out of 13 participants' motions only seven were reliable to use for the analysis. A similar problem appeared in Case B, but to a lower degree, and ten out of 12 tests could be analysed. This electromagnetic field sensitivity has been reduced in the last update of the Xsens MVN Studio software.

The methodology of comparing simulated motions with physical ones could have been used in multiple ways. The output from the biomechanical model from the IPS-HIRC software is joint angles for each of the joint segments creating the skeleton (in total 134 values). The Xsens Awinda system also outputs a similar sort of data with fewer data points (66 values). Since the RULA analysis was already implemented in the IPS-

HIRC software, the same function was also included to analyse the physical motions, and these data were then used in the evaluation of motion data.

The small number of physical test participants is a limiting factor for this verification study. It was difficult and time-consuming to do the physical test on the persons; each test took around 60 minutes. Access to the demonstration environments was also restricted, thus the number of potential tests was limited.

The selection of the manikin family in the verification could have been done differently. It is possible to create digital manikins that would represent the anthropometrics of the physical human performing the tests (Brolin et al., 2017). However, in creating HIRC simulations, a process that considers the variety of all humans is suggested, and in this process the characteristics of the future user of the workstation are not always known. Additionally, the workstation has to be a well-designed system even when new operators enter it. Thus a generic family is proposed when designing HIRC workstations and such a family was also used in this evaluation study. In this example a Swedish anthropometric database was used since both tests were performed in Sweden.

5 Conclusions

The aim of this paper is to verify the biomechanical load and operation time predicted by the human-industrial robot collaborative simulation software with results obtained from motions performed by humans. This was investigated through two industrial HIRC cases. In both cases two hypotheses were connected with the fidelity of the simulation software investigated. First that the biomechanical load in the simulation results is verified by physical experiments, and second that operation time results from the software are verified by physical experiments. The results show some correlation, mainly in the biomechanical load, while the assessed operation time from the simulation underestimates the experiments in these two cases. However, a large variation in physical data makes it difficult to draw definite conclusions from the analysis.

One important reason for the large variation is that the majority of the tests persons used for the physical test are not experienced operators. They are mainly university students with no or very limited experience from assembly tasks in industry. They lack the training to perform assembly tasks in a smooth and efficient way. This difference could actually be noticed visually in the data collection as four of our 25 test participants were from industry. In future evaluation studies another selection of operators would give more representative results and limit the variance in the participants' motions. If it is difficult to get the actual operators from the existing workstation, any experienced assembly operators should be just as good, as they have the accurate assembly skills and the potential to learn a new assembly task relatively fast. It would most likely demand an extensive practice with university students on a specific workstation before they develop a smooth and efficient way to perform a workstation task.

Another way to meet the difference in variation between the IPS-HIRC simulation software and the physical experiment is to include stochastic variables into the software in order to mimic human variation in performance. This could be done through addition of a distributed probability of human motions and paths that the manikin is likely to take and randomly select one for each motion (Shahrokhi and Bernard, 2009). This would of course imply that the idea of deterministic simulation in the IPS software environment (Högberg et al., 2016) is discarded.

One limiting factor in verification of HIRC workstations is the availability of HIRC workstations in industry or laboratory environments. This limitation affected the two cases used in this study. Neither of them is perfectly suitable to investigate the verification of human motions, as one includes visual inspection that is a vague and not well-defined process and the other includes a static process with a high risk of fumbling with the enabling device. There are, however, extremely few HIRC cases available in industry and lab environments that could be used for these tests. A proposed future work is to investigate the DHM part of the simulation software separately through verification and measurements on any kind of human manufacturing case and disregard the industrial robot part and in parallel with that perform similar measurements on industrial robots, comparing operation time between the software and physical robot programs. This would allow selection of manufacturing tasks more suitable for verification studies. Combining these would increase validity in the simulation software IPS IMMA and the HIRC part of the software.

In conclusion, this study verifies the simulation results from the human-industrial robot collaborative simulation software IPS-HIRC. Through two cases some improvement areas in the software were identified as well as methodological challenges in verifying simulation and real behaviour of humans in HIRC environments. Despite the low correlation, new hypothesis-driven verification studies with more appropriate cases are needed before any clear statements could be made on the time evaluation part of the software.

Acknowledgements

The contributions of Juan Luis Jiménez Sánchez (for simulation work in Case B) and Golshid Hadialhejazi (for assistance in performing physical experiments for Case A) were of importance and highly appreciated in the presented work. The authors are also grateful for the support from the Royal Institute of Technology (KTH) and Linköping University for access to their laboratories, which enabled the physical experiments to be performed. The research work was funded by the Swedish Knowledge Foundation (for the INNOFACTURE Research School), Scania and Mälardalen University. The research was also supported by the research project ‘Virtual Verification of Human Robot Collaboration’ and ‘ToMM2 – Future Collaborative Assembly Team of Man and Machine’, both funded by the Swedish Governmental Agency for Innovation Systems (VINNOVA). The research was conducted in the context of the XPRES research and education environment at Mälardalen University.

References

Baldwin, L.P., Eldabi, T., Hlupic, V. and Irani, Z. (2000) ‘Enhancing simulation software for use in manufacturing’, *Logistics Information Management*, Vol. 13, No. 5, pp.263–270.

Bauer, W. (Ed.), Bender, M., Braun, M., Rally, P. and Scholtz, O. (2016) *Lightweight Robots in Manual Assembly—Best to Start Simply!: Examining Companies’ Initial Experiences with Lightweight Robots*, Fraunhofer-Institut für Arbeitswirtschaft und Organisation IAO, Stuttgart, Germany.

Bertilsson, E., Hanson, L., Högberg, D. and Rhén, I.M. (2011) 'Creation of the IMMA manikin with consideration of anthropometric diversity', in Spath, D., Krause, T. and Ilg, R. (Eds.): *Proceedings of the 21st International Conference on Production Research (ICPR 21): Innovation in Product and Production*, Vol. 1, pp.416–420, Fraunhofer IAO, Stuttgart, Germany.

Bohlin, R., Delfs, N., Hanson, L., Högberg, D. and Carlson, J.S. (2012) 'Automatic creation of virtual manikin motions maximizing comfort in manual assembly processes', in Hu, S.J. (Ed.): *Technologies and Systems for Assembly Quality, Productivity and Customization. Proceedings of the 4th CIRP Conference on Assembly Technologies and Systems*, Ann Arbor, MI, USA, pp.209–212.

Brolin, E., Högberg, D., Hanson, L. and Björkenstam, S. (2017) 'Virtual test persons based on diverse anthropometric data for ergonomics simulations and analysis', in Osvalder, A-L., Blomé, M. and Bodnar, H. (Eds.): *Proceedings of the 49th NES 2017 Conference 'Joy at Work'*, Lund University, Lund, Sweden, pp.232–239.

Gopinath, V., Johansen, K. and Ölvander, J. (2018) 'Risk Assessment for Collaborative Operation: A Case Study on Hand-Guided Industrial Robots', in Svalova, V. (Ed.): *Risk Assessment*, IntechOpen, pp.167–187.

Hanson, L., Sperling, L., Gard, G., Ipsen, S. and Olivares Vergara, C. (2009) 'Swedish anthropometrics for product and workplace design', *Applied Ergonomics*, Vol. 40, No. 4, pp.797–806.

Hasselqvist, O., Söderström, P. and Wiklund, A. (1969) *MTM:s grundrörelser: definitioner och beskrivningar av MTM-systemets grundrörelser*, Svenska MTM-fören., Stockholm, Sweden.

Högberg, D., Hanson, L., Bohlin, R. and Carlson, J.S. (2016) 'Creating and shaping the DHM tool IMMA for ergonomic product and production design', *International Journal of the Digital Human*, Vol. 1, No. 2, pp.132–152.

IPS (2019a) *Industrial Path Solutions* [online] http://industrialpathsolutions.se/ (accessed 16 January 2019).

IPS (2019b) *IPS IMMA* [online] http://industrialpathsolutions.se/ips-imma/ (accessed 2 January 2019).

Khalid, O., Caliskan, D., Ore, F. and Hanson, L. (2015) 'Simulation and evaluation of industrial applications of human-industrial robot collaboration cases', in Fostervold, K.I., Kjøs Johnsen, S.Å., Rydstedt, L. and Watten, R.G. (Eds.): *Proceedings of NES2015: Nordic Ergonomics Society 47th Annual Conference, NEHF (Norwegian society for Ergonomics and Human Factors)*, Lysaker, Norway, pp.C5-1–C5-5.

Krüger, J., Nickolay, B., Heyer, P. and Seliger, G. (2005) 'Image based 3D Surveillance for flexible man-robot-cooperation', *CIRP Annals – Manufacturing Technology*, Vol. 54, No. 1, pp.19–22.

Laring, J., Forsman, M., Kadefors, R. and Örtengren, R. (2002) 'MTM-based ergonomic workload analysis', *International Journal of Industrial Ergonomics*, Vol. 30, No. 3, pp.135–148.

Mårdberg, P., Carlson, J.S., Bohlin, R., Delfs, N., Gustafsson, S., Högberg, D. and Hanson, L. (2014) 'Using a formal high-level language and an automated manikin to automatically generate assembly instructions', *International Journal of Human Factors Modelling and Simulation*, Vol. 4, Nos. 3/4, pp.233–249.

Marusteri, M. and Bacarea, V. (2010) 'Comparing groups for statistical differences: how to choose the right statistical test?', *Biochemia Medica*, Vol. 20, No. 1, pp.15–32.

Maynard, H.B., Stegemerten, G.J. and Schwab, J.L. (1948) *Methods-Time Measurement*, McGraw-Hill, New York, NY.

McAtamney, L. and Corlett, E.N. (1993) 'RULA: a survey method for the investigation of work-related upper limb disorders', *Applied Ergonomics*, Vol. 24, No. 2, pp.91–99.

Michalos, G., Makris, S., Tsarouchi, P., Guasch, T., Kontovrakis, D. and Chryssolouris, G. (2015) 'Design considerations for safe human-robot collaborative workplaces', *Procedia CIRP*, Vol. 37, pp.248–253.

Mourtzis, D., Papakostas, N., Mavrikios, D., Makris, S. and Alexopoulos, K. (2015) 'The role of simulation in digital manufacturing: applications and outlook', *International Journal of Computer Integrated Manufacturing*, Vol. 28, No. 1, pp.3–24.

Nachar, N. (2008) 'The Mann-Whitney U: a test for assessing whether two independent samples come from the same distribution', *Tutorials in Quantitative Methods for Psychology*, Vol. 4, No. 1, pp.13–20.

Ore, F. (2015) *Human-Industrial Robot Collaboration: Simulation, Visualisation and Optimisation of Future Assembly Workstations*, LIC thesis, Mälardalen University, Västerås, Sweden.

Ore, F., Hanson, L., Delfs, N. and Wiktorsson, M. (2015) 'Human industrial robot collaboration – development and application of simulation software', *International Journal of Human Factors Modelling and Simulation*, Vol. 5, No. 2, pp.164–185.

Ore, F., Reddy Vemula, B., Hanson, L. and Wiktorsson, M. (2016) 'Human-industrial robot collaboration: application of simulation software for workstation optimisation', in Söderberg, R. (Ed.): *Proceedings of the 6th CIRP Conference on Assembly Technologies and Systems (CATS), Procedia CIRP*, Vol. 44, pp.181–186.

Schepers, M., Giuberti, M. and Bellusci, G. (2018) *Xsens MVN: Consistent Tracking of Human Motion Using Inertial Sensing*, White paper, MV0424P.A, Xsens Technologies B.V., Enschede, the Netherlands.

Shahrokhi, M. and Bernard, A. (2009) 'A framework to develop an analysis agent for evaluating human performance in manufacturing systems', *CIRP Journal of Manufacturing Science and Technology*, Vol. 2, No. 1, pp.55–60.

Spensieri, D., Bohlin, R. and Carlson, J.S. (2013) 'Coordination of robot paths for cycle time minimization', in *2013 IEEE International Conference on Automation Science and Engineering (CASE 2013)*, IEEE, Madison, WI, pp.522–527.

Stopp, A., Baldauf, T., Hantsche, R., Horstmann, S., Kristensen, S., Lohnert, F., Priem, C. and Ruscher, B. (2002) 'The Manufacturing Assistant: safe, interactive teaching of operation sequences', in *IEEE ROMAN 2002. 11th IEEE International Workshop on Robot and Human Interactive Communication, Proceedings*, pp.386–391.

The Department of Defense Modeling and Simulation Enterprise Glossary [online] https://www.msco.mil/MSReferences/Glossary/TermsDefinitionsE-H.aspx (accessed 20 May 2021).

Tsarouchi, P., Makris, S. and Chryssolouris, G. 2(016) 'Human–robot interaction review and challenges on task planning and programming', *International Journal of Computer Integrated Manufacturing*, Vol. 29, No. 8, pp.916–931.

Vignais, N., Bernard, F., Touvenot, G. and Sagot, J-C. (2017) 'Physical risk factors identification based on body sensor network combined to videotaping', *Applied Ergonomics*, November, Vol. 65, pp.410–417.

Xsens (2019) *Xsens MTw Awinda* [online] https://www.xsens.com/products/mtw-awinda/ (accessed 2 January 2019).

Zhang, X. and Chaffin, D.B. (2005) 'Digital human modeling for computer-aided ergonomics', in Karwowski, W. and Marras, W.S. (Eds.): *Handbook of Occupational Ergonomics*, CRC Press, Boca Raton, FL, pp.1–20.

Appendix

In this process there is a need to interpret and adjust some RULA thresholds in the digital models to compute a grand RULA score (all text in italics below are quotations from the RULA employee assessment worksheet (McAtamney and Corlett, 1993)):

- *If shoulder is raised: +1*, interpreted as > 2° in the digital joint data.
- *If upper arm is abducted: +1*, interpreted as > 2° in the digital joint data.
- *If arm is supported or person is leaning: -1*, has to be manually inserted. In the cases presented in this paper there is no support for the human, thus this reduction of value is not valid.
- *If arm is working across midline of the body: +1*, interpreted as > 25° elbow angle in the digital joint data .
- *If arm out to side of body: +1*, interpreted as > 2° in the digital joint data.
- *Locate Wrist Position, neutral position* interpreted as > -2° and < 2° in the digital joint data.
- *If wrist is bent from the midline: +1*, interpreted as < -2° and > 2° in the digital joint data.
- *If wrist is twisted mainly in mid-range =1*, mid-range interpreted as > -90° and < 90° in the digital joint data.
- *Add Muscle Use Score*, has to be manually inserted. In the cases presented in this paper there are no static or repetitive tasks, thus this value is set to 0.
- *Add Force/Load Score*, has to be manually inserted. In the cases presented in this paper the loads are lower than 2 kg, thus this value is set to 0.
- *Locate Neck Position, in extension*, interpreted as > 2° in the digital joint data.
- *If neck is twisted: +1*, interpreted as < -2° and > 2° in the digital joint data.
- *If neck is side-bending: +1*, interpreted as < -2° and > 2° in the digital joint data.
- *Locate Trunk Position, neutral position* interpreted as < 2° in the digital joint data.
- *If trunk is twisted: +1*, interpreted as < -2° and > 2° in the digital joint data.
- *If trunk is side-bending: +1*, interpreted as < -2° and > 2° in the digital joint data.
- *If legs & feet supported and balanced: +1, If not: +2* has to be manually inserted. In the cases presented in this paper the legs and feet are supported, thus this value is set to 1.