Using Time-Based Musculoskeletal Risk Assessment Methods to Assess Worker Well-Being in Optimizations in a Welding Station Design

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Abstract

Simulation using virtual models is used widely in industries because it enables efficient creation, testing, and optimization of the design of products and production systems in virtual worlds. Simulation is also used in the design of workstations to assess worker well-being by using digital human modelling (DHM) tools. DHM tools typically include musculoskeletal risk assessment methods, such as RULA, REBA, OWAS, and NIOSH Lifting Equation, that can be used to study, analyse, and evaluate the risk of work-related musculoskeletal disorders of different design solutions in a proactive manner. However, most musculoskeletal risk assessment methods implemented in DHM tools are in essence made to assess static instances only. Also, the methods are typically made to support manual observations of the work rather than by algorithms in a software. This means that, when simulating full work sequences to evaluate manikins' well-being, using these methods becomes problematic in terms of the legitimacy of the evaluation results. In addition to that, to consider objectives in optimizations they should be measurable with real numbers, which most of musculoskeletal risk assessment methods cannot provide when simulating full work sequences.

In this study, we implemented the musculoskeletal risk assessment method OWAS in a digital tool connected to the DHM tool IPS IMMA. We applied the Lundqvist index on top of the OWAS whole body risk category score. This gave us an integer of the time-based ergonomic load for a specific simulation sequence, enabling us to qualitatively compare different design solutions. Using this approach, we performed an optimization in a welding gun workstation to improve the design of the workstation. The results show that using time-based musculoskeletal risk assessment methods as objective functions in optimizations in DHM tools can provide valuable decision support in finding solutions for workstation designs that consider worker well-being.

Keywords: Ergonomics, Simulation, Time-based, Evaluation, Optimization

Introduction

Simulation using virtual models is used widely in industries because it enables efficient creation, testing, and optimization of the design of products and production systems in virtual worlds (Fisher et al., 2011; Kuhn, 2006; Oppelt & Urbas, 2014). Simulation is also used in the design of workstations to assess worker well-being by using digital human modelling (DHM) tools. One development of DHM tools in recent years is that many DHM tools, such as Siemens Jack (Raschke & Cort, 2019), IPS IMMA (Hanson et al., 2019) and Santos (Abdel-Malek et al., 2019), now can predict and represent human motions, enabling simulations of full motion sequences.

DHM tools typically include musculoskeletal risk assessment methods, such as RULA (Rapid Upper Limb Assessment) (McAtamney & Nigel Corlett, 1993), REBA (Rapid Entire Body Assessment) (Hignett & McAtamney, 2000), OWAS (Ovako Working Posture Assessment System) (Karhu et al., 1977), and NIOSH (National Institute for Occupational Safety and Health) Lifting Equation (Waters et al., 1993), that can be used to study, analyse, and evaluate the risk of work-related musculoskeletal disorders (WMSDs) of different design solutions in a proactive manner. However, most musculoskeletal risk assessment methods implemented in DHM tools are in essence made to assess static instances only (Berlin & Kajaks, 2010). Also, the methods are typically made to support manual observations of the work rather than by algorithms in a software. This means that, when simulating full work sequences to evaluate manikins' well-being, using these methods becomes problematic in terms of the legitimacy of the evaluation results. In addition to that, to consider objectives in optimizations the results of the musculoskeletal risk assessment methods should be measurable with real numbers, which most of them cannot provide for complete motions.

This paper investigates how to implement a time-based musculoskeletal risk assessment method in DHM based simulations of motion sequences, and how outcomes from the method can be used within objective functions in optimizations. In order to test and illustrate, the approach is implemented in a use case from industry, representing a manual welding workstation.

Methods

A case study was used to test and illustrate time-based musculoskeletal risk assessment methods in optimizations. The case study and the modelling in a DHM tool, representation of anthropometric diversity, ergonomics assessments by OWAS Lundqvist index, and the optimization definitions, are described in the following subsections.

Case study and modelling in IPS IMMA

The case study represents a manual welding task within manufacturing at Volvo Cars in a factory located in China. This task involves the use of a welding gun to weld two parts together. Since the gun is supported by a lifting device, workers are not affected by the weight of the gun. Inertia effects from moving the guns are not considered in this study. The DHM tool IPS IMMA (Hanson et al., 2019) was used to model the workstation and the welding task performed by the workers (Figure 1).

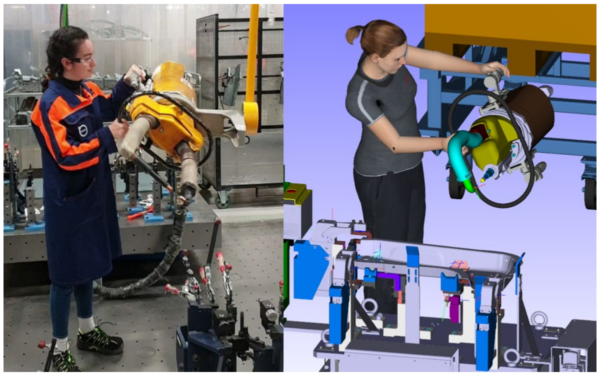

Figure 1. Real workstation (left) and corresponding model of the workstation in IPS IMMA (right)

The welding gun can be grasped in different positions, and the welding can be performed in different angles if the welding gun is kept perpendicular to the welding spot (Figure 2). The geometry of the workstation can cause collisions with the welding gun and limits the possible angles of welding (Figure 3).

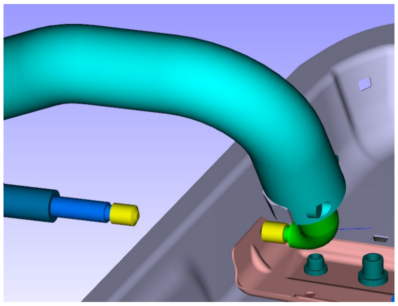

Figure 2. Perpendicular welding position of the welding gun

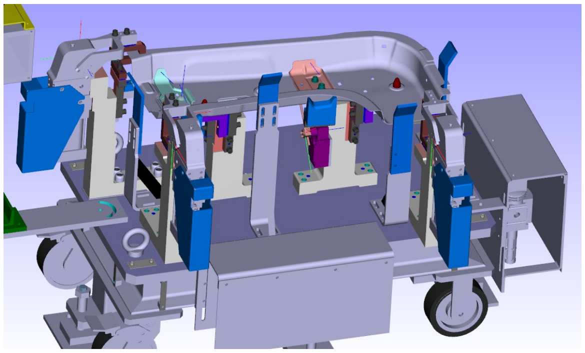

Figure 3. Geometry of the welding workstation

The welding gun motion is planned with a path planning algorithm in IPS IMMA (Hanson et al., 2019) to enter to the welding position in a valid path without considering the manikin well-being. This motion requires the manikin rotating and placing the welding gun (Figure 4).

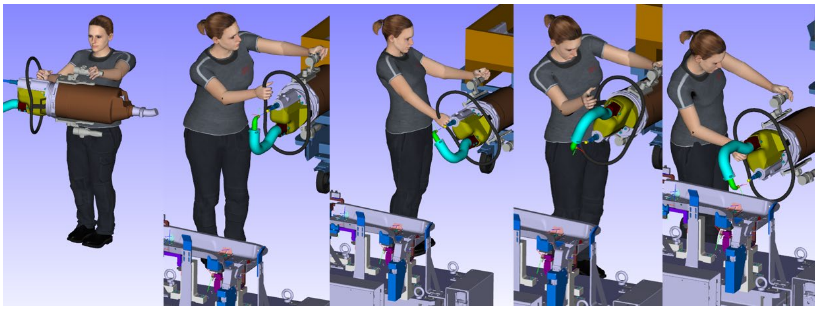

Figure 4. Welding motion modelled in IPS IMMA

Representation of anthropometric diversity

The factory of the use case is located in China. A manikin family was created to represent the anthropometric variation in stature and elbow height, which were considered two key anthropometric measures of this workstation. The CAESAR database on Asian population (SAE International, 2022) was used to obtain anthropometric data of 176 individuals (83 male and 93 female). This data was used to create two confidence ellipsoids, one for males and one for females, both with a confidence interval of 95% (Brolin et al., 2012). Using the method described in Högberg et al. (2011), considering axial and centre cases of both ellipsoids, a family of 10 manikins (Table 1) was created in IPS IMMA (Figure 5).

Table 1. Anthropometric measures of the manikins

Nº Case	Gender	Stature	Elbow Height

		(mm)	(%-ile)	(mm)	(%-ile)
Case 0 (Median)	Female	1571.16	50.00	964.27	50.00
Case 1	Female	1711.24	99.19	1064.66	99.19
Case 2	Female	1431.09	0.81	863.88	0.81
Case 3	Female	1598.02	67.76	945.02	32.24
Case 4	Female	1544.31	32.24	983.51	67.76
Case 5 (Median)	Male	1698.93	50.00	1040.37	50.00
Case 6	Male	1875.53	99.22	1164.28	99.22
Case 7	Male	1522.33	0.78	916.47	0.78
Case 8	Male	1727.50	65.21	1020.33	34.79
Case 9	Male	1670.35	34.79	1060.42	65.21

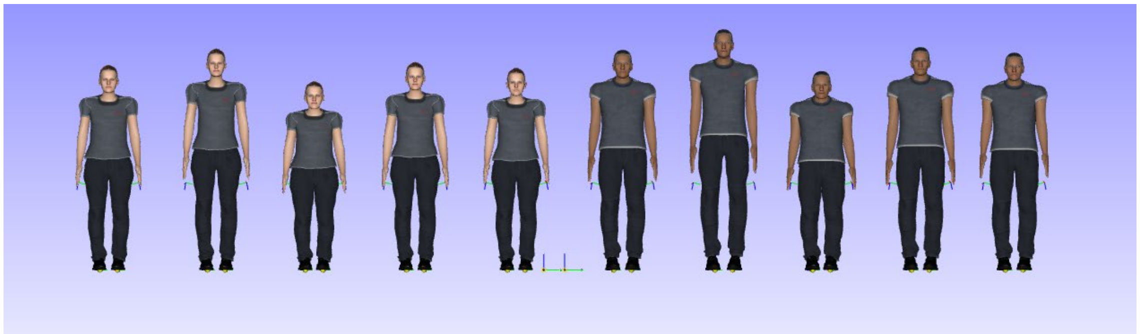

Figure 5. Cases 0 to 9 modelled in IPS IMMA

Ergonomics assessments by OWAS Lundqvist index

Ovako Working posture Analysing System (OWAS) is an musculoskeletal risk assessment method used to classify working postures of the *Back*, *Arms*, *Legs*, and *Use of force* (Karhu et al., 1977; Louhevaara et al., 1992). OWAS is based on the classification of 84 basic work postures, covering common and easily identifiable work postures. The *Use of force* category is classified into three levels, meaning that there are 252 possible combinations in total, each resulting in a unique OWAS code consisting of four digits. Each OWAS code results in one of four possible action categories, representing the risk level for WMSDs: 1 (*green, no corrective measures*), 2 (*yellow, corrective measures in the near future*), 3 (*orange, corrective measures as soon as possible*), and, 4 (*red, corrective measures immediately*) (Karhu et al., 1977; Louhevaara et al., 1992). The OWAS method provides the assessment of postural load over time, but only on sublevel, i.e. on the specific back, arms and legs postures separately (Karhu et al., 1977; Louhevaara et al., 1992). In order to make OWAS a time-based musculoskeletal risk assessment method able to indicate ergonomic load on an aggregated level, i.e. considering both working postures of the back, arms, legs, and use of force, in an integrated manner, the OWAS method can be complemented with the Lundqvist index (Lundqvist, 1988; Pinzke, 2016). This is a cumulative load index that helps to assess the workload over time. The index is represented by a number from 100 (meaning that 100% worktime is in action category 1) up to 400 (meaning that 100% worktime is in action category 4). Hence, higher values of the Lundqvist index represent a higher risk of developing WMSDs. The Lundqvist index method provides no action levels however. Still the method can be used to qualitatively assess different design solutions from the perspective of risks for WMSDs, as well as in objective functions in optimization.

Optimization definition

The optimization variable defined for this case is the welding angle. The welding angle has been defined without considering collision with the workstation. This allows to explore solutions that could be more beneficial for the well-being of the manikins but would be in collision with the actual design of the workstation.

When the angle is changed, the simulation is run again for the entire manikin family, and the OWAS Lundqvist index values are sent to the optimization algorithm for it to define the welding angle for the next iteration. There are ten manikins, which provide ten OWAS Lundqvist index values that form the ten optimization objectives to minimize for the use case, which makes the optimization problem a multi-objective optimization. The optimization algorithm NSGA-II (Deb et al., 2002) was used for this use case due to its efficiency in multi-objective optimizations and has been run for 100 iterations.

Results

After performing the optimization, the results were analysed and interpreted to obtain more insights of how the time-based method behaved in the optimization, as well as of the workstation design itself.

Optimization results

For every iteration the welding gun angle was changed by the optimization algorithm, making the 10 manikins perform the welding in different postures. In order to perform the welding in different postures, the entire motion of the welding gun changed by using the input of the optimization algorithm implemented in the optimization platform (Iriondo Pascual et al., 2022) and the path planning algorithm of the DHM tool (Figure 6).

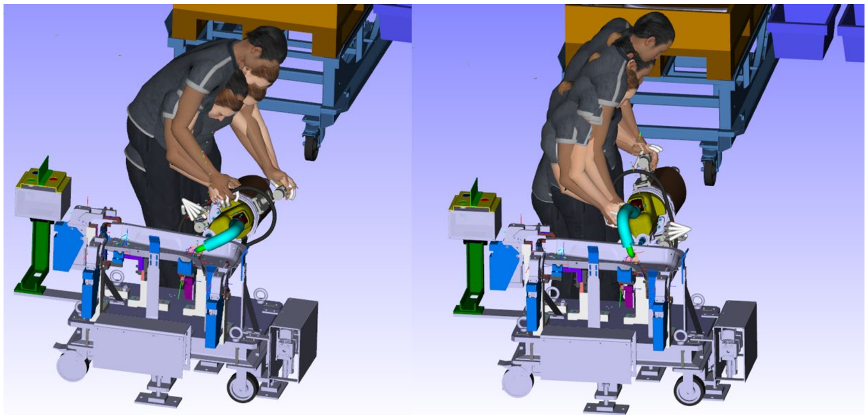

Figure 6. Different positioning of the welding gun provided by the optimization platform

After finishing all the iterations, the results of the OWAS Lundqvist index for every manikin and welding gun positioning were analysed. The results show that some manikins obtained higher values of OWAS Lundqvist index than others (Figure 7).

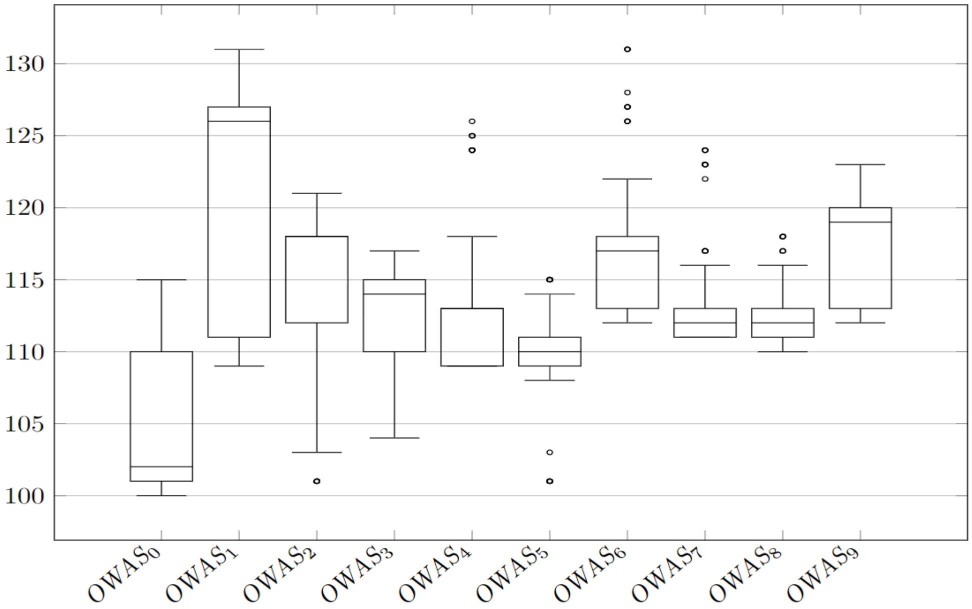

Figure 7. OWAS Lundqvist index result for each manikin

The results also showed low correlation between the optimization variable, i.e. the welding gun angle, and the objectives, i.e. OWAS Lundqvist index. For example, for manikin 0, the results show that there are two main clusters in the OWAS Lundqvist index values, and that the lowest values in both clusters were for a welding gun angle between 50-80° and 160-170° (Figure 8).

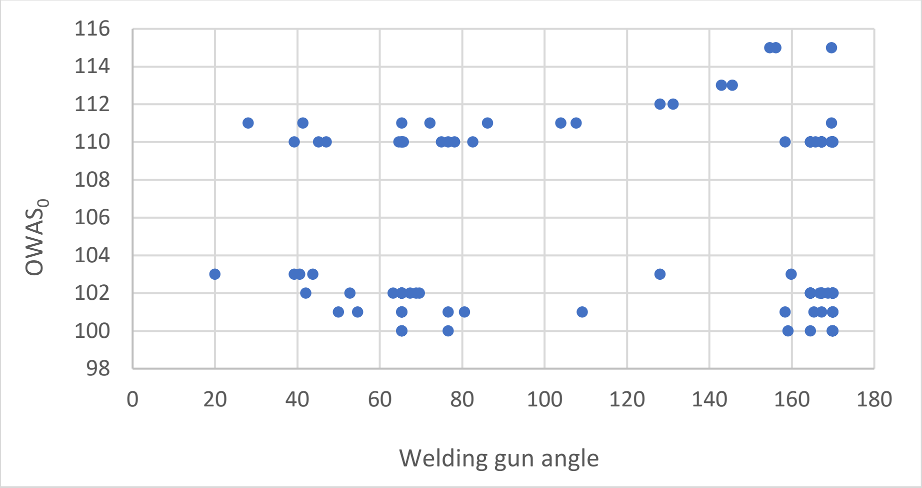

Figure 8. OWAS Lundqvist index results for manikin 0 depending on the welding gun angle

For some manikins (e.g. manikins 1, 2 and 3) the results for the welding gun angles are directly related, and the positioning of the gun provide either higher or lower OWAS Lundqvist index values equally for them (Figure 9).

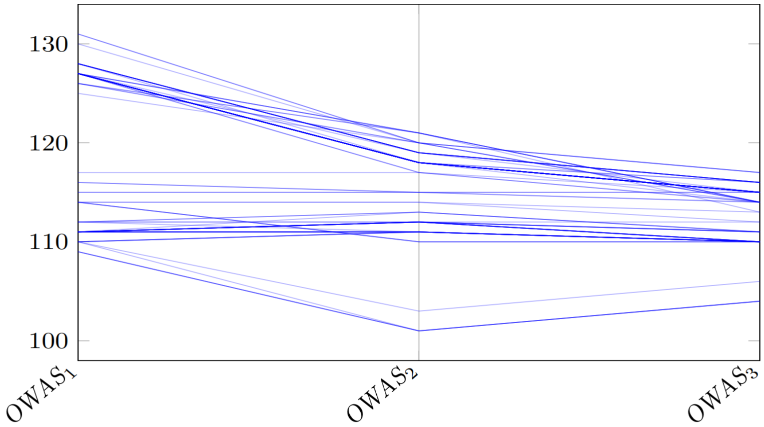

Figure 9. Direct relationship of OWAS Lundqvist indexes of manikins 1, 2 and 3

However, in some cases (e.g. manikins 0 and 1) the welding gun angles that can be positive for one manikin can be negative for the other manikin (Figure 10).

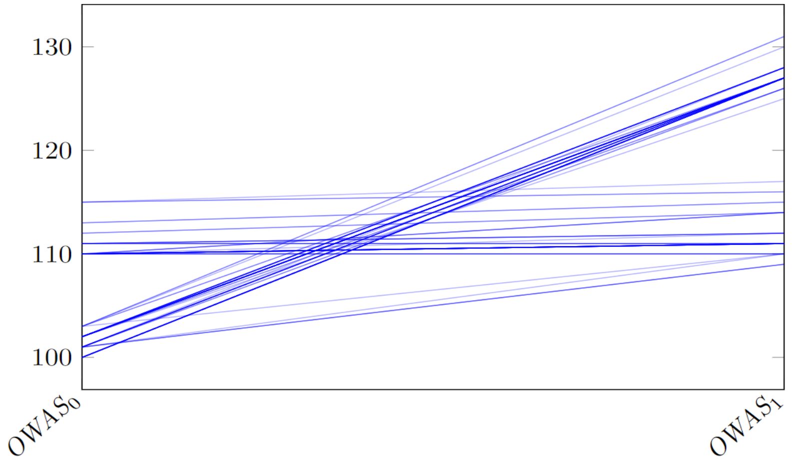

Figure 10. Inverse relationship of OWAS Lundqvist indexes of manikins 0 and 1

Interpretation of results

The results show that some manikins got higher OWAS Lundqvist index values. If we relate the values (Figure 7) to the anthropometric measures of the manikins (Table 1) the results show higher values for the manikins with a higher stature, especially for the female manikin 1 and for the male manikin 6. These manikins correspond to the higher axial cases in both stature and elbow height for female and male populations. These results (Figure 7) show that even in the best positioning they can have worse postures than lower stature manikins.

When analysing manikins individually, two clusters are found in all the cases. For example, in Figure 8 the clusters for manikin 0 are over the OWAS Lundqvist index scores 110 and under 104. When analysing the resulting simulations it can be seen that the cluster with the highest values was created by simulations where manikins could not obtain a proper positioning to hold the welding gun, e.g., simulations where manikins stopped grasping the welding gun.

Some welding positions that gave low OWAS Lundqvist index values had collision with the geometry of the workstation. Hence, they could not be achieved with the actual design of the workstation (Figure 11). However, as it might be possible to resolve the collisions by redesign of the workstation, we set up the optimization to include also solutions with collision, since that can be valuable information to the designer.

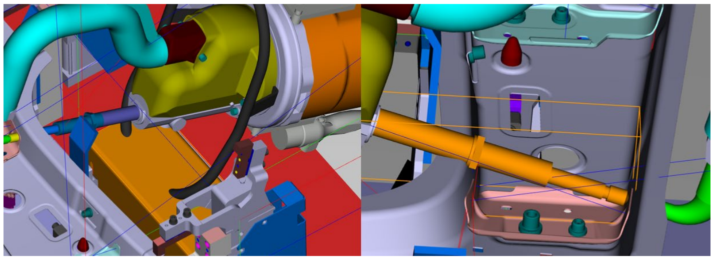

Figure 11. Positioning of the welding gun in collision with the workstation geometry

Discussion and Conclusions

Designing a workstation considering workers' well-being in DHM tools requires using musculoskeletal risk assessment methods that can assess the risk of workers developing WMSDs. Using time-based musculoskeletal risk assessment methods, like the one provided by combining OWAS with Lundqvist index, in DHM tools allows users to analyse complete motions of manikins in simulations instead of single postures. The analysis allows finding out if performing the motions enhances the risk of developing WMSDs. With common single posture ergonomics evaluation methods, such as RULA (McAtamney & Nigel Corlett, 1993) and REBA (Hignett & McAtamney, 2000), there is a possibility to choose the wrong postures to assess, and therefore, underestimate the risk of performing certain operations. With time-based ergonomics evaluation methods all the postures in the motion are evaluated, leading to a lower risk of evaluating the wrong postures, as well as considering the aggregated load. However, using time-based ergonomics evaluation methods requires the motions of the manikins to be representative of how real humans perform work tasks.

The musculoskeletal risk assessment method OWAS Lundqvist index has been found to be appropriate to use together with optimization algorithms. OWAS Lundqvist index provides a single integer per manikin as an optimization objective, which allows using the integers as objective functions in optimization algorithms. In this case, ten manikins were used to represent the anthropometric diversity at the workstation, i.e. resulting in a ten objective optimization problem, and a single optimization variable, i.e. the welding angle. The results show a relation between the anthropometric measures of the manikins and the OWAS Lundqvist index values, obtaining the highest risk scores in the manikins with highest stature and elbow height values. In addition to that, the optimal welding positions for different manikins are different, meaning that there is a risk of designing a workstation that would hinder individuals in the population to perform the work with an appropriate work posture, and therefore increase their risk of developing WMSDs, should the designer only consider one or a few manikins. In this study some beneficial welding positions were found in collision, therefore, modifying the design of the workstation to allow these positions could enable workers to perform the welding task with lower risk to develop WMSDs.

In conclusion, implementing time-based musculoskeletal risk assessment methods in optimizations in DHM tools allows users to perform optimizations of workstation designs where full work sequences are simulated. The optimizations could be performed for any design parameter, e.g., layout, tool positioning, and task order, and use time-based musculoskeletal risk assessment methods to assess the worker well-being. In addition to that, anthropometric diversity can be included to assess the level of inclusion of the workplace, and by that supporting a sustainable work life for all members of the workforce, basically by assisting designers to find better workstation design solutions. This study has been limited to one time-based musculoskeletal risk assessment methods, i.e., OWAS Lundqvist index, however, other time-based musculoskeletal risk assessment methods should be studied to find the most appropriate ones for the task assessed. Also, this study did not consider productivity metrics, but future work will include system performance metrics such as cycle time, spaghetti diagram, and value adding time, added to the optimization. Optimising both human well-being and system performance is in-line with the definition and purpose of ergonomics

Acknowledgments

This work has been supported by ITEA3 in the project MOSIM, the Knowledge Foundation and the associated INFINIT research environment at the University of Skövde, within the Virtual Factories with Knowledge-Driven Optimization (VF-KDO) research profile and the Synergy Virtual Ergonomics (SVE) project, and by the participating organizations. Their support is gratefully acknowledged.

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