Title:

Multi-directional one-handed strength assessments using AnyBody Modeling Systems.

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Highlights:

- This work investigates the use of musculoskeletal modeling to estimate strength.
- It focuses on the strength variation in diverse hand locations and force directions.
- A literature strength database was used as reference for the simulations.
- Isometric strength was simulated at 8 hand locations and in 26 exertion directions.
- Correlation coefficient of 0.7 was observed between simulated and empirical data.

Abstract:

Digital human modeling tools support proactive ergonomics in optimizing work tasks and workplace layouts. Empirical-statistical model based tools are often used to estimate the force exertion capability of the operators. This work is intended to serve as an initial probing into the usability of a musculoskeletal model based software, AnyBody Modeling Systems (AMS), in evaluating the force exertion capability at different points in the workspace and for various exertion directions. As a first step, it focuses on the modeling approach and the accuracy of one-handed isometric strength estimates of AMS. An existing literature database was used to compare the predicted strength at 8 hand locations and in 26 exertion directions, while simulating the empirical postures. The results show a correlation coefficient of 0.7 between the simulated and the experimental strength. AMS emphasizes the biomechanical advantages in strength due to the alignment of force exertion direction with the shoulder. Additionally, some discrepancies have been identified and discussed.

Keywords:

Musculoskeletal modeling, workplace optimization, standing exertion

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1.0 Introduction

Proactive ergonomics targets the prevention of work-related musculoskeletal disorders (WMSDs) through early detection and reduction of risk factors at work, such as awkward postures and excessive force exertion. Nowadays, Digital Human Modeling (DHM) tools support proactive ergonomics through virtual simulations of work tasks and workplace during the design phase (Longo and Monteil, 2011; Spada et al., 2017; Summerskill et al., 2016; Van Houcke et al., 2017). These tools integrate several analyses such as reachability, visibility, clearance and ergonomic risk assessment, amongst others to evaluate the various workplace alternatives. The aim of these analyses is to optimize the workplace and mitigate the risks of WMSDs, such as those due to awkward postures and excessive force exertion. To this last aim, the knowledge of population strength capabilities is crucial to lowering the risk due to overexertion (Lin et al., 2013), which is also exemplified by the ongoing research in this field (Ekşioğlu, 2016; Plewa et al., 2016; Thompson et al., 2015). Equally, it is critical that the DHM tools are able to model correctly the force exertion capabilities in different workplace layouts, i.e., accounting for changes in work location and exertion directions, to suitably optimize the workplace layout in proactive ergonomics (La Delfa and Potvin, 2017).

There could be two approaches to compare the acceptability of alternative workplace layouts in DHM tools: empirical-statistical modeling and musculoskeletal modeling. The prior consists of well-known software programs like 3DSSPP and Jack and makes use of a static strength model (Chaffin et al., 2006) to evaluate the reactive body joint moments due to the work task requests. These joint moments are compared with empirical population strength databases to estimate the population percentile capable of performing the task. The percentile capable is widely used to compare the work task demands in alternative layouts (Bertoloni et al., 2012; Tripathi et al., 2015; Zhang et al., 2013). The latter approach, i.e. musculoskeletal modeling, consisting of software such as AnyBody Modeling Systems (AMS), uses mathematical modeling techniques to simulate the diverse muscles and bones in the human musculoskeletal structure. Muscles are modeled as contractile force generating elements, while bones as rigid elements. Each muscle in the model is assigned a strength based on its size and its contribution towards performing a work task is determined by the solution of an optimization problem in an inverse dynamics analysis (Damsgaard et al., 2006). The ratio between the muscle contribution and its corresponding strength, that is the muscle activation level, has been used to compare the acceptability of alternative workplace layouts (Pontonnier et al., 2014; Xu et al., 2016).

There are clear differences between empirical-statistical and musculoskeletal modeling approaches to estimate the strength of the digital human. The reliability of empirical-statistical models depends significantly on the breadth of the empirical observations as a variety of working conditions can be observed in the workplace. Therefore, a crucial concern with the empirical-statistical model based DHM tools is how they extrapolate the strength to conditions that were not part of the observed set. On the other hand, musculoskeletal model based DHM tools should be able to account for this diversity in the working conditions if they represent a detailed and more realistic model of the human musculoskeletal structure. The key aspects of musculoskeletal models are the accuracy of the muscle models and the correct utilization of muscles in a given task. The human body consists of more muscles than necessary to perform a task. Therefore, it is fundamental that the model simulates correctly the criterion selected by the central nervous system (CNS) to decide the utilization of the various muscles to perform a given task.

In this work, we attempt to assess the usability of AMS as a tool for workplace optimization. The utility of a proactive tool for workplace optimization would depend on the accuracy of the predicted force exertion capability, the convenience in setting the mannequin into desired postures, and the scaling of the strength to represent different population percentiles. The aim of this work is to serve as a first step to investigate the reliability of defining favorable directions of force exertion at different work points through AMS to support virtual workplace optimization. In other words, we would like to verify if the human model of AMS could reliably account for the variation in the human force exertion capability due to changes in the work location and exertion direction. We would use the isometric strength at the hand as a measure of the force exertion ability due to the vast existing literature and ease in simulation. The existing work using AMS in simulations of isometric force exertion is focused on unidirectional exertions. Bassani et al., (2017) and Rajaee et al., (2015) simulated lifting loads to compare the predicted lumbar intradiscal pressure with *in vivo* measurements. Duprey et al., (2015) simulated the medial force at the hand during a hose insertion task. Oomen et al., (2015) developed a rule for strength scaling based on the knee extension strength and validated the simulated leg press strengths using this rule. While AMS has shown good results in these specific applications, the behavior of AMS in a general application of multi-directional isometric force exertions is unknown to the best of the authors' knowledge.

For its use as a tool for workplace optimization, it would be useful if the human model of AMS can represent a population sample. The use of population sample is important as ergonomists usually compare task requirements with the capabilities of the population to estimate the risk of WMSDs (La Delfa and Potvin, 2017). Therefore, we would use the average strength, anthropometric and posture data of a population sample as a reference for the simulations. The approach for modeling the population strength is different from modeling individual strength, which requires detailed subject-specific data, beyond the usual anthropometric variables (Oomen et al., 2015). Thus, the purpose of the present study is to evaluate whether the multi-directional force exertion capability in the workspace, as assessed by the AMS human model, can reliably simulate the strength capabilities of a population sample.

2.0 Material and Methods

As this work focused on the isometric strength assessments of AMS in the workspace, it was important to have detailed knowledge and to reproduce the postures of the subjects to reduce the variation in strength due to unequal postures. We searched existing strength databases in the literature to use as a reference for the simulations. However, several multi-directional strength databases lacked specific postural information such as the joint angles assumed by the subjects during the trials. La Delfa and Potvin, (2016), Roman-Liu and Tokarski, (2005) and the master's thesis of La Delfa, (2011) provided such strength databases with explicit postural information. Roman-Liu and Tokarski, (2005) measured gripping, lifting, and pushing forces and torques of pronation and supination. This was a limited set of exertions when compared to (La Delfa and Potvin, 2016) and La Delfa (2011), both of which measured force exertion in 26 directions at eight hand locations. Between both of these works, La Delfa, (2011) had a more extensive posture database encompassing all the test conditions (8 hand locations * 26 directions = 208) by averaging the joint angles across the subjects only. Instead, La Delfa and Potvin, (2016) provided the same joint angles at only the eight hand locations, averaging across subjects as well as exertion directions at every hand location. Additionally, the subjects were standing during the strength tests in La Delfa, (2011). Whereas, in La Delfa and Potvin, (2016), the subjects were seated during the trials. The use of a seat would allow the subjects to brace themselves against the additional surfaces of the seat, augmenting the strength in directions favorable to such bracing. Simulating such an interaction would introduce additional uncertainties in the results of the simulation. Consequently, La Delfa (2011) was selected as the reference database. This database provided the necessary information to develop the simulations in AMS. A summary of the key aspects of these experiments is provided in this section. For more details, the reader is referred to the original work of La Delfa (2011).

2.1 Experimental Data

Seventeen right-handed female subjects were recruited for the experiments that required them to exert maximal isometric force using their right hand in a standing posture while using their left hand to support and brace themselves during the exertion. The mean height of these subjects was 167.7 cm (SD ± 6.8), the mean weight was 62.5 kg (SD ± 10.9), and the mean age was 24 years (SD ± 1.8).

The eight hand locations in these experiments were defined using the height of the hand relative to the body and the horizontal hand angle (Figure 1a). The hand heights (overhead, shoulder, and umbilicus) were uniquely defined for every subject, considering their respective anthropometry. The horizontal hand angles (0°, 45°, and 90°) were the angles that a vertical plane passing through the hand and the shoulder subtended with a sagittal plane through the shoulder. The eight hand locations used in the experiments were Overhead 0°, Overhead 45°, Shoulder 0°, Shoulder 45°, Shoulder 90°, Umbilicus 0°, Umbilicus 45°, and Umbilicus 90°. The third coordinate of the hand location, that is the distance of the hand from the shoulder, was defined as 80% of the maximum arm reach.

At each hand location, the subjects exerted force in 26 directions. These 26 directions were classified as one-dimensional (1D), two-dimensional (2D) or three-dimensional (3D). 1D directions were the six primary directions (Superior, Inferior, Anterior, Posterior, Medial, and Lateral). 2D and 3D directions were the combinations of two or three of these 1D directions, respectively (La Delfa and Potvin, 2016). We adopted the same naming convention for force exertion directions in this work and they are illustrated in Figure 1b.

Force or manual arm strength (MAS) of the subjects was measured using a triaxial load cell mounted with a vertically oriented handle. A live feedback was provided to the subjects during the experiments that enabled them to monitor and control the force exertion vector. The subjects' posture was recorded using an optical motion capture system and three joint angles of the right upper limb were provided in the database. These were the horizontal and vertical shoulder angle, and the elbow flexion angle. Horizontal shoulder angle was defined as the angle formed by the upper arm on a horizontal plane such that an angle of 0° meant that the upper arm is abducted laterally, while an angle of 90° meant that the upper arm was flexed forward. Vertical shoulder angle was defined as the angle that the upper arm subtended with a vertical line passing through the shoulder.

2.2 Musculoskeletal modeling

A detailed review of AMS is available in Damsgaard et al., (2006). While AMS itself is a modeling software, its developers also built a human model using the software. Dimensions of muscles, bones, and their corresponding connecting locations are some of the basic data that is required to develop the mathematical model and it is sourced from cadaver studies. This human model along with its documentation and a few starting templates are available in the AnyBody Managed Model Repository (AMMR), which is supplied along with AMS. AMS uses inverse dynamics analysis to calculate internal body forces based on known kinematics and external forces on the body. The common usage of AMS is to start with one of the available templates and develop it further to simulate the user's application.

AMS version 6.0.7 was used to develop static simulations of the experiments. The Human Standing template from the AMMR version 1.6.5 was developed further to simulate the average posture for each trial. The mannequin was scaled to the mean height and weight of the 17 subjects using the length-mass-fat scaling law (Rasmussen et al., 2005). The basic body model, with respect to the number of muscles and their attachment points on the bones, remains the same for both the male and the female mannequins. However, the scaling changes the size of the bones, the mass distribution, and the fat percentage differently for the male and the female mannequins. The female mannequin provided in the AMMR only accepted percentile based scaling. While percentile based scaling is very useful to represent a population sample in an application of workplace optimization, it is inconvenient when a custom height and weight must be used for scaling. We checked and found a significant difference in the absolute values of strength between a male and a female mannequin for a given hand position and force exertion. However, there was a negligible influence on the variation of strength due to changes in hand location and/or exertion direction between the male and female mannequin such that the strength ratio between the male and the female remains almost constant at all directions and hand locations. Consequently, a male mannequin was chosen, which also allowed scaling according to a custom height and weight.

After the anthropometric scaling, the development of the model required simulation of the correct posture, inverse dynamics analysis, and strength scaling. These steps are described in the subsequent sections.

2.2.1 Posture

Often in proactive ergonomics during the design stage, the postures adopted by the operator to perform a work task must be estimated from the location of the work point relative to the operator. Therefore, a posture prediction algorithm, such as the one in 3DSSPP, is useful for the ergonomist to quickly drive the mannequin into the posture the operator is likely to assume. Although advantageous, such a posture prediction algorithm is not available as default in AMS. However, AMS provides an optimization routine that the users could exploit to optimize or predict the posture by defining a function to optimize. Literature has several examples of this so-called inverse-inverse dynamics approach where the body joint angles have been optimized in static as well as dynamic activities (Farahani et al., 2015a, 2015b, 2015c). In the context of the current work, Farahani et al., (2015b) is of interest. They used AMS to predict the shoulder abduction angle when the hand was subjected to isometric inferior direction forces of varying magnitude. While these references show the potential of AMS in predicting postures, the aim of the present work required that the posture of the mannequin matched the average posture of the population sample to limit the errors in the predicted strength due to unequal postures between the simulation and the empirical trials. Therefore, we adjusted the mannequin manually to match the given postures.

The shoulder-arm system of the mannequin consisted of seven degrees of freedom (DOF), requiring an equal number of constraints for the complete definition of the posture of the upper limb. There are three DOFs at the shoulder (abduction, flexion, and rotation of the upper arm), two at the elbow (flexion and pronation), and two at the wrist (flexion and deviation). The average vertical and horizontal shoulder angles and the elbow flexion angle from La Delfa (2011) provided two constraints at the shoulder (abduction and flexion) and one at the elbow (flexion) for all the 208 test conditions. The vertical handle on the load cell provided two more constraints: elbow pronation and wrist deviation. The upper arm rotation was driven from the horizontal angle of the hand location using an optimization study in AMS, such that a vertical plane passing through the hand and the shoulder subtended the corresponding angle (0°, 45° or 90°) with the sagittal plane. Finally, the wrist flexion was left unconstrained to avoid calculation of unrealistic postures. In theory, the 80% arm reach could have provided the seventh constraint required to calculate the wrist flexion angle. However, the required precision for adding the seventh constraint was not available. While three of the previous six DOFs have been driven using empirical measurements, the other three DOFs have been driven by the constraints assumed for the experiments. It is likely that there were some deviations from these conditions, which are typical during experimental trials. As these deviations could not be verified, the errors between the simulated and the real posture in these three and the final DOF would have compounded and reflected solely in the final DOF. Therefore, an unrealistic wrist flexion angle could have been calculated in several trials. Unfortunately, the experimental wrist flexion angles were not available and it was concluded that the required precision for adding the seventh constraint was not obtainable. By default, the wrist flexion was defined as 0° and, subsequently, the actual wrist flexion and the percentage arm reach were measured from the simulations to check for anomalies.

There was no precise information regarding the posture of the left arm. Some pictures of the experimental setup and trials provided an approximate posture of the left arm. This was utilized to roughly model the left arm posture. The left hand was simulated as fixed to the frame, thus allowing its contribution during the force exertion.

2.2.2 Inverse dynamics analysis

The inverse dynamics analysis of AMS calculates the muscle forces required to maintain the mannequin in the defined posture, while subjected to external loads. The strength of the mannequin is estimated when at least one of the muscle reaches its maximum possible contribution. Therefore, the strength of the mannequin depends on the strength of each muscle in the body and the muscle recruitment criterion, which controls the activation level of each muscle in a given task.

The strength and the behavior of the muscle model should be representative of the corresponding real muscle. In the human model of AMS, the ideal strength of each muscle depends on its corresponding physiological cross-sectional area (PCSA), which has been sourced from various cadaver studies. Then, there are models with different level of details to simulate the working behavior of the muscle model in AMS, i.e. to simulate the effect of the working conditions of the muscle on its ideal strength. We used the 3-element (3E) model, which is the most detailed model available in the software and is based on the modified Hill muscle model introduced by Zajac, (1989).

The muscle recruitment criterion of AMS aims to simulate the CNS in identifying the muscles that should be used in a given work task. It is a problem of redundancy as the human body contains more muscles than necessary to perform a given task and it could be challenging to replicate precisely the criterion chosen by the CNS, especially the utilization of antagonistic muscles (Ting et al., 2012). For example, the co-contractions of antagonistic muscles are needed to stabilize joint motions and depend on the required accuracy of motion (Gribble et al., 2003). The muscle recruitment problem in AMS is solved as an optimization problem that minimizes an objective function subject to certain constraints. The muscle recruitment criterion used in our simulations is the min/max criterion (Rasmussen et al., 2001). It defines the objective function to be minimized as the maximum of normalized muscle forces:

$$G\left(\boldsymbol{f}^{(\boldsymbol{M})}\right) = \max\left(\frac{f_i^{(M)}}{N_i}\right), \quad i = 1, \dots , n^{(M)} \tag{1}$$

Subjected to the following constraints:

$$C\boldsymbol{f} = \boldsymbol{r} \tag{2}$$

$$\left(f_i^{(M)}\right) \geq 0 \; ; \; i \in \left\{1, \dots, n^{(M)}\right\} \tag{3}$$

where G is the objective function of the recruitment strategy stated in terms of the muscle forces, $\boldsymbol{f}^{(M)}$. N_i is a measure of the muscle's strength at the current working conditions. $n^{(M)}$ is the number of muscles. $C = [C^{(M)}C^{(R)}]$ is the coefficient-matrix of the unknown forces vector, $\boldsymbol{f} = [\boldsymbol{f}^{(M)T}\boldsymbol{f}^{(R)T}]^T$. Superscripts (M) and (R) designate terms related to muscle forces and joint reactions, respectively. Instead, $\boldsymbol{r}$ is a vector of the known external and inertial forces. The constraint (3) restricts the muscles to pulling only and prevents pushing.

The normalized muscle force, $(f_i^{(M)})/ N_i$, is also known as the muscle activity. This ratio defines the current activation level of the muscles. The min/max criterion tends to group muscles at different muscle activity levels. It results in the sharing of load by multiple synergistic muscles forming an activity level group in a way that the muscles share the same activity level and contribute correspondingly to their individual strengths (Rasmussen et al., 2009). No other muscle recruitment strategy can reduce the muscle activity further. The min/max criterion has also been previously noted as a minimum fatigue criterion (An et al., 1984). The maximum of the muscle activities, considering all the muscle groups in the human model, is known as the maximum muscle activity (MMA). The MMA represents the maximum muscle activation in the model and can be interpreted as the percentage of maximum possible contraction required to balance the external loads. Therefore, MMA $= 1$ would represent the maximum possible contraction and, correspondingly, the strength of the mannequin in this work.

To simulate the force exertion by the mannequin in a given direction, an arbitrary external force was applied on the right hand in a direction opposite to the required exertion direction. The inverse dynamics analysis resulted in the output of muscle forces and the MMA of the model. As MMA = 1 signifies a condition of maximum contraction of the corresponding muscles and consequently a condition of MAS for the mannequin, the magnitude of the applied external force was divided by the resultant MMA value to obtain the force magnitude for which the MMA should equal unity. This resultant force magnitude was noted as the MAS of the mannequin.

As mentioned in section 2.2.1, the left hand of the mannequin was simulated as fixed to the frame. This allowed the software to utilize the left arm to support the mannequin when subjected to the load at the right hand. The software calculated the unknown reaction force at the left hand as a solution to the equilibrium equations of the complete system. Naturally, the left arm formed a part of the same human model and was subjected to the same muscle model and muscle recruitment criterion as the rest of the human model. Therefore, the calculated reaction force at the left hand was normalized by the MMA just as in the case of MAS calculation.

2.2.3 Strength scaling

Although the muscle strength is scaled by the length-mass-fat scaling law (Rasmussen et al., 2005), AMS additionally allows scaling just the strength as per the user's requirements. While AMS permits the user to modify the strength of each muscle, even though this option is advisable only when specific data are known, it is important to clarify here that we scaled the strength as a global factor for all the muscles in the model. This would be the general use in ergonomic workplace optimization. Also, in this way, the scaling affects the strength of all the muscles uniformly and it does not affect the response of the model to changes in work points and exertion directions, which is the focus of this work.

Therefore, the simulations were initially performed with anthropometric scaling only. A ratio of four was observed between the average simulated MAS and the average empirical MAS. Thus, the strength of the model was further scaled down by a factor of four to match the average strength of the subjects to facilitate the comparison. This method of scaling using empirical strength may seem to favor the results of the simulations, however, we verified that the correlation coefficient between the predicted and empirical strength remains constant prior to and after the strength scaling. Thus, the results reported in section 3.0 are the predicted values after the strength scaling.

Currently, there is no method of estimating the population strength capabilities in AMS. The strength in AMS is not based on a statistical database and the user is expected to scale the strength of the model based on known values. The absolute values of the strength, which can be scaled easily in the software, is not the central aspect of this work. These values could be scaled by comparing the strength of the mannequin with those of the desired strength percentile from a chosen database in a database-defined posture. However, often, the ergonomist must evaluate conditions that are not specified in the selected database. Indeed, the focus in the current work is on the ability of AMS to vary the strength due to changes in hand location and exertion direction. This should help the ergonomist to extrapolate reliably the strength of the mannequin to work conditions not covered in the selected strength database and to identify favorable conditions for workplace optimization. In addition to the strength, joint reaction forces and joint moments, AMS provides information about muscle activation and synergy that could be useful for the ergonomist in estimating fatigue and optimizing the workplace.

2.3 Statistical analysis

Pearson's correlation coefficient was used to compare the empirical MAS and the simulated MAS from AMS. A correlation of $r \geq 0.9$ is classified as a good prediction, r = 0.7 – 0.89 a moderate prediction, and r = 0.5 – 0.69 a poor prediction (Vincent, 2005). In addition, the root mean square error (RMSE) was also evaluated for comparison with 3DSSPP strength predictions as reported in La Delfa (2011). These statistical parameters were chosen to ensure consistency with the statistical analysis performed in La Delfa (2011).

3.0 Results

The overall correlation between the AMS simulated MAS and the empirical values was moderate with $r = 0.714$ ($p < 0.01$) (Figure 2). The predicted reaction forces at the left hand ranged from 2.0 to 8.5% of the body weight with a mean value of 5.6%.

Figure 3 shows the average MAS value and the directions with the maximum and the minimum MAS for the empirical and simulated data. At all the hand locations, the maximum MAS values are more distant from the mean as compared to the minimum values for both the empirical and the simulated data, except for the simulated data at Umbilicus 0°. This indicates the presence of directions that are favorable to force exertion at every hand location. However, the strongest exertion directions between the experimental and the simulated data correspond at only four hand locations. The same is also true for the weakest exertion directions, where two of these hand locations (Shoulder 45° and Umbilicus 90°) show simultaneous correspondence between the most and the least favorable exertion directions.

Figures 4, 5, and 6 show the detailed comparison between all the empirical and simulated MAS values. These radar charts group the exertion directions in four vertical planes passing through the right hand, such that each vertical plane consists of eight coplanar exertions. These planes could be parallel to the sagittal plane (Vertical 0) or rotated clockwise in increments of 45° (Vertical 45, Vertical 90, and Vertical 135). It is evident from figures 4, 5 and 6 that the simulated MAS in the Superior direction is overestimated at Overhead 0°, Shoulder 0°, and Umbilicus 0° hand locations. The charts for Overhead 45 Vertical 90, Shoulder 90 Vertical 0, Umbilicus 45 Vertical 135, and Umbilicus 90 Vertical 0 show a good match between the curves of the empirical and the simulated MAS. The charts for Shoulder 0 Vertical 0 and Umbilicus 45 Vertical 45 show the existence of opposite directions in which force exertion peaks, although both of these charts also show a shift in the orientation of the directions with peak forces between the empirical and simulated MAS curves.

4.0 Discussion

The present study is meant as a first step to assess the usability of AMS as a tool for proactive engineering. It also adds to the validation literature of AMS in an application of multi-directional isometric strength prediction at the dominant hand and provides insights into its response to changes in hand locations and exertion directions.

Based on the overall correlation coefficient (r = 0.714), it can be said that the model of AMS is responsive to changes in postures and exertion directions (figure 2). The shapes of the curves formed by the simulated and the empirical MAS also reflect this (figures 4, 5 and 6). Although the curves were not coincident, they had similar shapes in a few cases. However, there were also significant differences in the prediction of AMS in some other cases. This section elaborates further on these results.

4.1 Comparison of strength predictions of AMS and 3DSSPP.

As mentioned in section 1.0, there are differences between empirical-statistical and musculoskeletal modeling approaches to estimate the strength. Literature indicates the limitations of the strength prediction model of 3DSSPP due to its limited strength database, which must be corrected for postures and combined for different joint axes (La Delfa and Potvin, 2017), and due to its independent treatment of the moments about the three shoulder axes (Hodder et al., 2016). A simple example could be the change in shoulder flexion strength with the change in the shoulder abduction angle. The statistical extrapolations could likely be erroneous if the combined effect of these two aspects was not considered during their development. On the other hand, a detailed musculoskeletal model should be robust enough to account for these variations.

The current study shows an improvement of prediction results (r = 0.714; RMSE = 26.5% of mean strength) as compared to the 3DSSPP predictions (r = 0.305; RMSE = 45% of mean strength) reported in La Delfa (2011). Although the improvement is significant, it must be analyzed critically. There are two aspects that could influence a fair comparison between the results of the two software. Firstly, the dataset for the validation of 3DSSPP was different from that used in this study. La Delfa (2011) combined his MAS results at the eight hand locations with those at 36 other previously collected hand locations for the validation of 3DSSPP. Moreover, he validated 3DSSPP strength predictions in the six 1D exertion directions only. Consequently, 3DSSPP predictions were validated with 264 data points, while AMS predictions were validated with 208 data points, of which only 48 data points were common to both the software. Secondly, the predicted postures from 3DSSPP were used in its strength predictions. The predicted postures were obtained by inserting the empirical hand coordinates in the software and were not manipulated further to replicate the common usage of 3DSSPP by ergonomists. However, the posture prediction algorithm of 3DSSPP does not consider force exertion in its input and is unable to reflect the effects of force exertion on the predicted postures (Hoffman et al., 2009). Thus, the predicted postures of 3DSSPP could be different from the postures adopted by the subjects during the MAS trials. Depending on these differences in postures, there could be errors in the strength predicted by 3DSSPP as posture affects strength capabilities (Chow and Dickerson, 2009; Garg et al., 2005; Haslegrave et al., 1997; La Delfa and Potvin, 2016; Roman-Liu and Tokarski, 2005; Wilkinson et al., 1995). Therefore, the improvement of AMS in strength prediction over 3DSSPP cannot be concluded entirely due to the robustness of musculoskeletal modeling over empirical-statistical modeling.

4.2 Shoulder and elbow moment arms of the resultant force vector

Figure 3 shows that at every hand location, there is at least one direction that favors the force exertion capability. LaDelfa (2011) reported that the strongest exertion directions tended to be aligned with the arm, as also observed by Jan Nijhof and Gabriel, (2006) and La Delfa and Potvin, (2016). These directions were associated with a low moment arm of the exerted force vector about the shoulder.

It is critical for proactive ergonomics that the model of AMS recognizes correctly such exertion directions as well as the advantage in these directions. It is clear from figure 3 that the strongest exertion directions coincided in only half the hand locations, while AMS overestimated the maximum strength in all the hand locations. This aspect was further investigated by calculating the 3D shoulder and elbow moment arms of the force vector in every simulation. Figures 7 and 8 plots these moment arms for the MAS curves (from figures 3, 4, and 5) having the strongest exertion directions at each hand location. The corresponding MAS curves are also shown in the figures to allow a qualitative investigation that could explain some of the anomalies observed in the results. Figure 7 groups hand locations where the maximum empirical and simulated MAS directions coincide:

- Overhead 45°: Clear strength peaks can be seen in both the MAS curves. AMS mildly overestimates the strength at these peaks. These peaks are along directions that are simultaneously aligned with both the shoulder and the elbow.
- Shoulder 45°: The most favorable direction is aligned with the elbow in both the MAS curves, although shoulder alignment results in a comparable MAS correspondingly in both the curves. However, unlike the empirical MAS curve, the simulated MAS curve estimates an equal biomechanical advantage in the opposite directions.
- Shoulder 90°: The maximum MAS direction is aligned with the shoulder. This direction is also favored by low elbow moment arms. However, the simulated MAS along In/Me and Su/La, both of which also have low elbow moment arms, are overestimated.
- Umbilicus 90°: As in the case of Shoulder 45°, the maximum MAS is aligned along the direction with low elbow moment arm. Simultaneously, the directions aligned with the shoulder have nearly the same strength as those with elbow alignment. In all of these four directions, the simulated MAS matches closely with the empirical MAS.

Instead, Figure 8 groups hand locations where the maximum empirical and simulated MAS directions do not coincide:

- Overhead 0°: The favorable directions are aligned with both the elbow and the shoulder. While the maximum empirical MAS is along Su/An, the maximum simulated MAS is exactly opposite to it, receptive to similar biomechanical advantages.
- Shoulder 0°: A clear misalignment between the empirical and simulated strength peaks can be seen. While the most favorable empirical directions are aligned with the shoulder, the strongest simulated exertion directions are aligned with the elbow. Also, this is the only hand location where the simulated strengths along the directions with shoulder alignment are significantly underestimated.
- Umbilicus 0°: The maximum empirical MAS direction is aligned with the elbow and the directions with shoulder alignment have similar strengths, just as in the case of Shoulder 45° and Umbilicus 90°. However, the maximum simulated MAS is along the Superior direction due to a peculiar behavior of the AMS model (discussed further in section 4.3). As can also be seen at Overhead 0° and Shoulder 0°, the simulated superior direction strength is overestimated by AMS, despite the lack of shoulder or elbow alignments.
- Umbilicus 45°: Misaligned strength peaks can be observed between the simulated and empirical MAS curves. The empirical MAS peaks are along the directions with shoulder alignment, whereas, simulated MAS peaks are along the directions with elbow alignment. Nonetheless, the simulated MAS along the directions with shoulder alignments are in close agreement with the corresponding empirical MAS.

To sum up, the AMS model emphasizes the biomechanical advantage due to the alignment of force exertion direction with the shoulder. It also seems to provide significant biomechanical advantage to force alignment with the elbow. However, the latter postulate is not concretely evidenced in the literature to the best of the authors' knowledge.

4.3 Overestimation of strength in the Superior direction at 0° hand locations

The predicted superior direction strength was overestimated at Overhead 0°, Shoulder 0°, and Umbilicus 0° hand locations, as also noted in Section 4.2. Notably, these locations are characterized by the hand placed in front of the body. Instead, at the corresponding 45° and 90° hand locations, with the hand positioned laterally, the predicted superior direction strengths matched with the empirical strengths. Increasing the horizontal angles of the hand location does not necessarily involve asymmetry of the trunk, as also implemented in the current simulations. We checked the percentage arm reach, the wrist flexion and radial deviation angles in these simulations and could not find a systematic trend to justify the difference in the superior direction strength between the central (0°) and the lateral (45° and 90°) hand locations as predicted by the AMS human model.

Instead, we found further evidence in literature in support of the empirical results. Sanchez and Grieve, (1992) obtained similar results to La Delfa (2011) and concluded that the isometric superior direction strength is only weakly dependent upon the horizontal angle of the hand location. Figure 9 plots the empirical and simulated MAS in the superior direction at all the eight hand locations, along with the superior direction MAS at the closest locations from Sanchez and Grieve, (1992). It shows that the strength in the superior direction is anomalously overestimated by the AMS at all the 0° hand locations. Further, in the case of lifting activities, Marras and Davis, (1998) observed that spinal loads did not increase significantly for one-handed lifting when the horizontal hand angle is increased if the same hand as the side of lift location is used to execute the lift.

A previous study using AMS and replicating the conditions observed in this study could not be found. However, there are a few studies on dynamic lifting. Jiang and Sengupta, (2012) simulated the two-handed symmetric and asymmetric lifting tasks reported in Marras and Davis, (1998) using AMS. They found that the simulated peak compression and lateral shear forces at the L5/S1 joint decreased with increasing asymmetry, in contradiction with the results of the EMG-assisted model reported in Marras and Davis (1998). However, in other studies, AMS has shown good correlation with EMG data in dynamic two-handed symmetric lifting (Stambolian et al., 2016) and with *in vivo* intradiscal pressure in various static and dynamic activities including lifting and holding loads (Bassani et al., 2017; Rajaee et al., 2015).

4.4 Limitations

The possible deviations between the experiments and their simulations could affect the results presented in this study. As mentioned in section 1.0, a subject-specific modeling could have improved the strength predictions. However, this was not the scope of the study. We focused on modeling the average strength of a population sample, which could be useful in the ergonomic design and optimization of the workplace.

AMS had difficulties in solving the postures for some of the directions at the Overhead 0° hand location. In particular, AMS could not solve the postural constraints for the anterior, posterior, superior/anterior, and anterior/medial directions. The kinematic analysis for these directions resulted in an error or an incorrect solution for the shoulder location. However, the problems with the Overhead 0° hand location were not isolated to AMS only. This hand location was also the most difficult during the empirical trials. La Delfa (2011) reported the maximum variance of the 3D location of the shoulder during the trials at the Overhead 0° hand location. The lowest number of valid trials at the same hand location further support the difficulties faced by the subjects during the trials. Further investigation of the failed simulations revealed that the empirical posture angles for these directions were too extreme for AMS. Decrements in the horizontal and vertical shoulder angles resulted in the progress from an unrealistic posture to an error in the kinematics analysis, and eventually to a regular solution. Maximum corrections were required in the superior/anterior direction, where the input horizontal and vertical shoulder angles were reduced by 3.2° and 3.1°, respectively. To estimate the influence of these deviations of posture on the simulated MAS, we performed several other trials where we varied the shoulder angles by a few degrees and monitored the resultant MAS. We found that the change in MAS was less than 5% and, therefore, used the MAS values from the slightly deviated postures as it is.

Moreover, while the presence of bracing is known to increase force exertion capabilities (Jones et al., 2013), corresponding data of the reaction forces at left hand was not available in La Delfa, (2011). We could not find empirical measurements in similar test setups in the literature to assess whether the simulated reaction forces were reasonable. Similar percentages of body weight were reported in Godin et al., (2008) although they were measured during some common automotive assembly tasks.

5.0 Conclusions

This work is meant as a first step to assess the usability of AMS as a workplace optimization tool with a focus on the accuracy of the strength predictions of AMS. In particular, we sought to evaluate whether the human model of AMS may account for the variation in force exertion capability of a population sample due to changes in the working point and the exertion directions. We utilized a strength database from literature, which was chosen for its completeness also in the postural data of the subjects. We reproduced as accurately as possible the average posture of the population sample from the experiments to reduce the error due to unequal postures. The results showed a Pearson's correlation coefficient of 0.7 between the strength predicted by the mathematical model of AMS and the empirical data, indicating that the predictions of AMS can be trusted to an extent. The results also indicated towards possible improvements of the musculoskeletal model of AMS over the empirical statistical model of 3DSSPP, although, the predictions of AMS benefitted from the use of true postures. In any case, it is worth reminding that the two software are very different in terms of their complexity and target users.

It is crucial that AMS is able to identify favorable and unfavorable force exertion directions for its use in proactive ergonomics to mitigate the risks of WMSDs due to overexertion. AMS proved responsive to the biomechanical advantages in the force exertion capability due to the alignment of the exertion direction with the shoulder. However, AMS results showed an even greater advantage due to the alignment with the elbow rather than the shoulder. The biomechanical advantage of elbow alignment lacks sufficient evidence in the literature to support the increase in strength predicted by AMS. Another concern brought forward by the results was the overestimation of the Superior direction (or lifting) strength at all the three hand heights when the hand is located in front of the body as compared to lateral hand positions. Ultimately, AMS could identify the most favorable force exertion direction at only half of the eight hand locations evaluated in this study.

In short, we believe a model using AMS could support workplace optimization. Its outputs such as muscle activation, joint reaction forces and joint moments in the various work conditions could provide useful information for an ergonomist. However, additional work is required to investigate further the discrepancies identified in this initial study. Subsequently, modules of posture prediction and population strength capability could be developed to improve the usability in proactive ergonomics.

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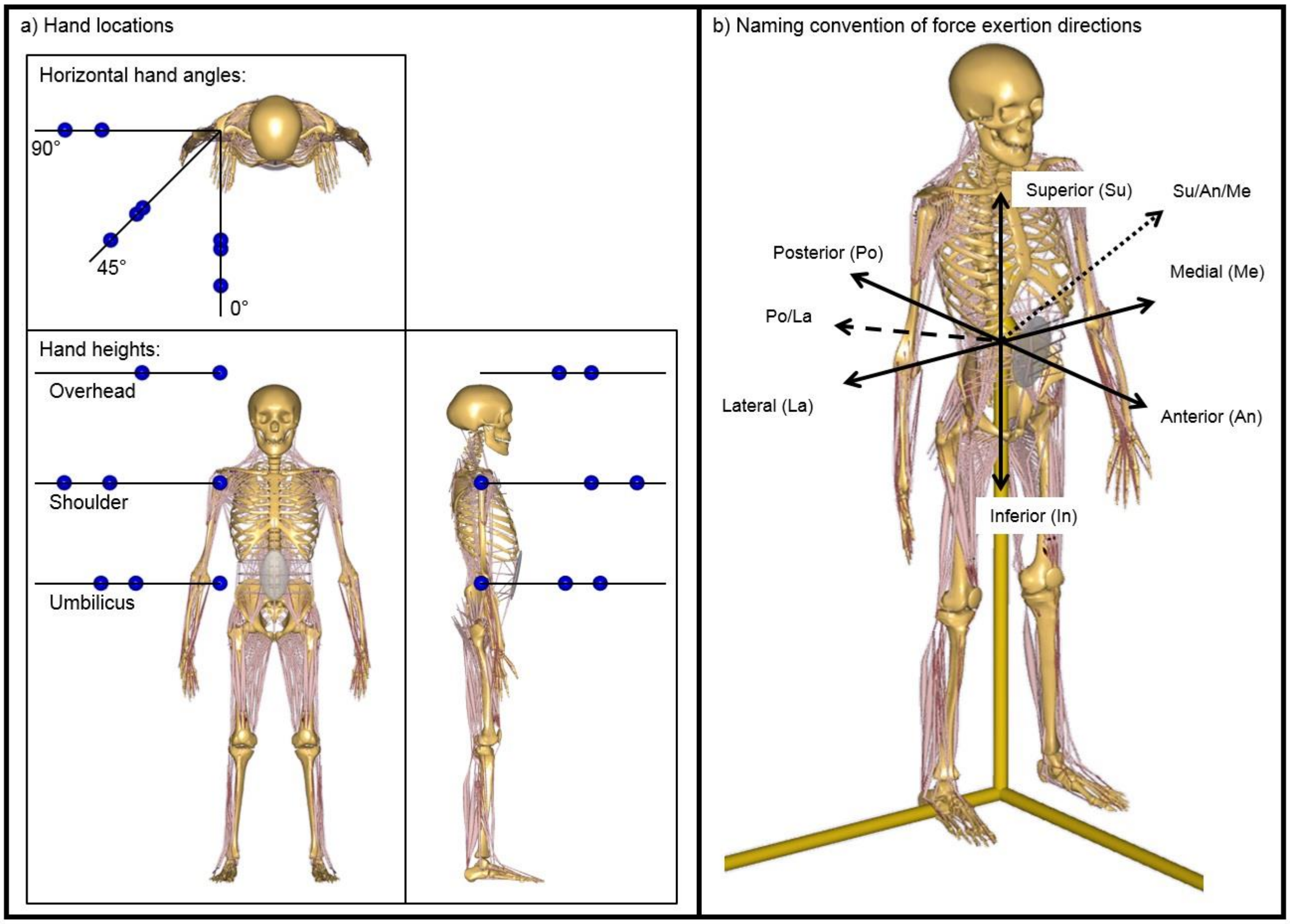


Figure 1: Illustration of a) hand locations and b) naming convention of the force exertion directions (adopted from La Delfa and Potvin, (2016)). Solid lines represent the six primary 1D directions. Dashed (Po/La) and dotted (Su/An/Me) lines are examples of 2D and 3D directions, respectively. Directions are reported using the first two letters of the corresponding 1D directions (Superior, Inferior, Anterior, Posterior, Lateral, and Medial).

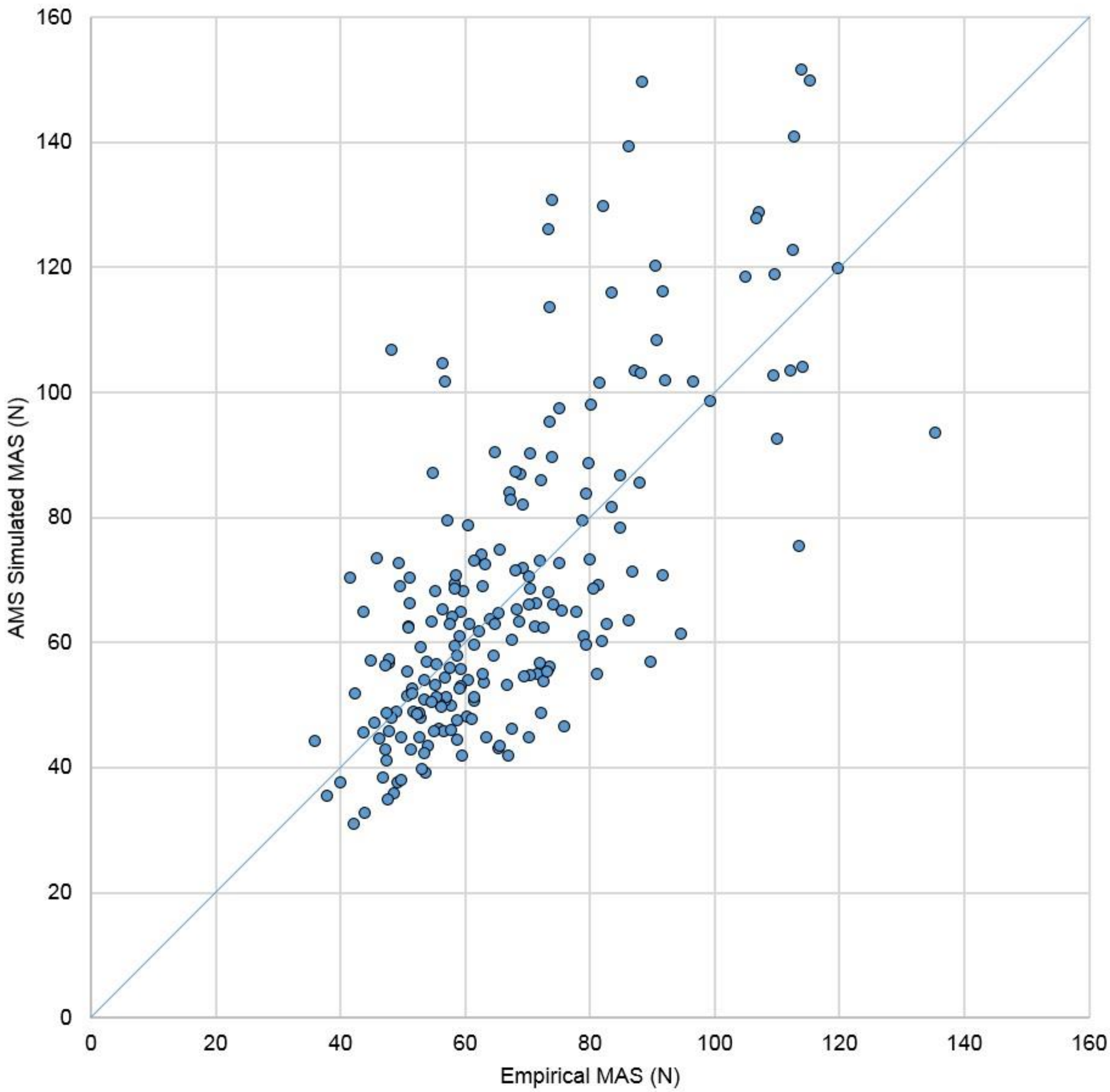
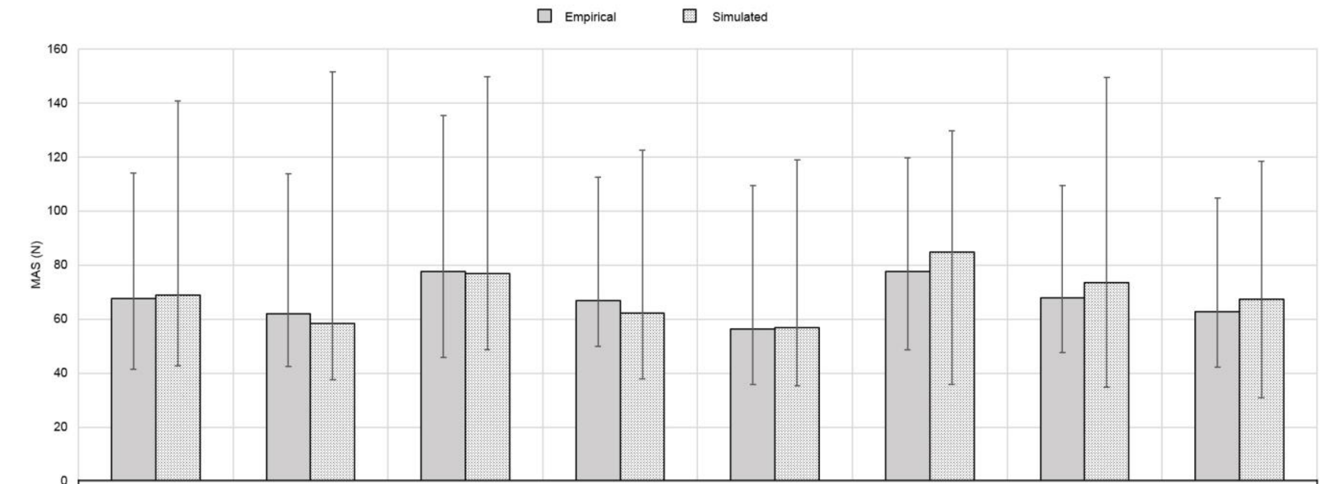


Figure 2: Overall correlation ($r = 0.714$; $p < 0.01$) between the Empirical MAS from La Delfa (2011) and the Simulated MAS of AMS. The bisector shows perfect match.



	Overhead 0		Overhead 45		Shoulder 0		Shoulder 45		Shoulder 90		Umbilicus 0		Umbilicus 45		Umbilicus 90	
	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated
Max MAS Direction	Su/An	In/Po	**In/Po/Me**	**In/Po/Me**	Po	In/Po	**In/Po/Me**	**In/Po/Me**	**Me**	**Me**	Po	Su	Su/Po/Me	Po/Me	**Me**	**Me**
Min MAS Direction	Su/Po	La	Su/Po	Po/La	Su/La	An/La	**Po/La**	**Po/La**	Su/Po	Po	**La**	**La**	**Po/La**	**Po/La**	**Po/La**	**Po/La**

Figure 3: Average MAS at each hand location. Error bars indicate the range of the data. The directions with maximum (Max) and Minimum (Min) MAS are reported for each hand location. Directions in bold highlight a concurrence between the empirical and the simulated directions.

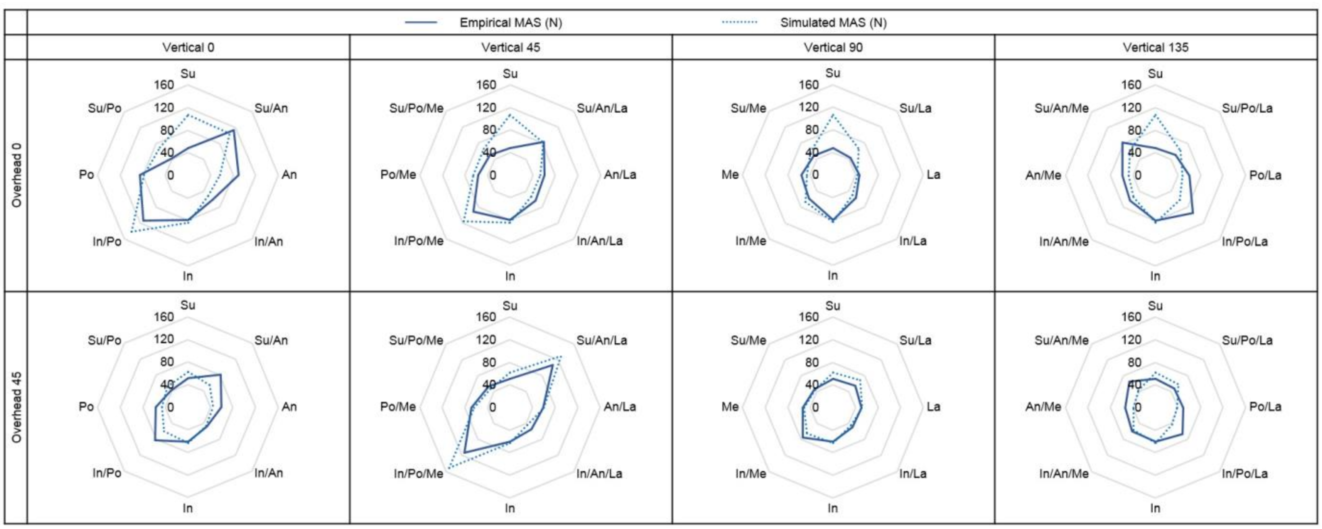


Figure 4: Radar charts showing the empirical (solid lines) and simulated (dotted lines) MAS (in Newtons) at the overhead hand locations. The 26 force exertion directions are grouped into 4 vertical planes centered at the right hand. The plane Vertical 0 is parallel to the sagittal plane. The planes Vertical 45, Vertical 90, and Vertical 135 are rotated by 45°, 90°, and 135°, respectively, in the clockwise direction from the plane Vertical 0. Each plane plots the MAS of its 8 coplanar exertion directions.

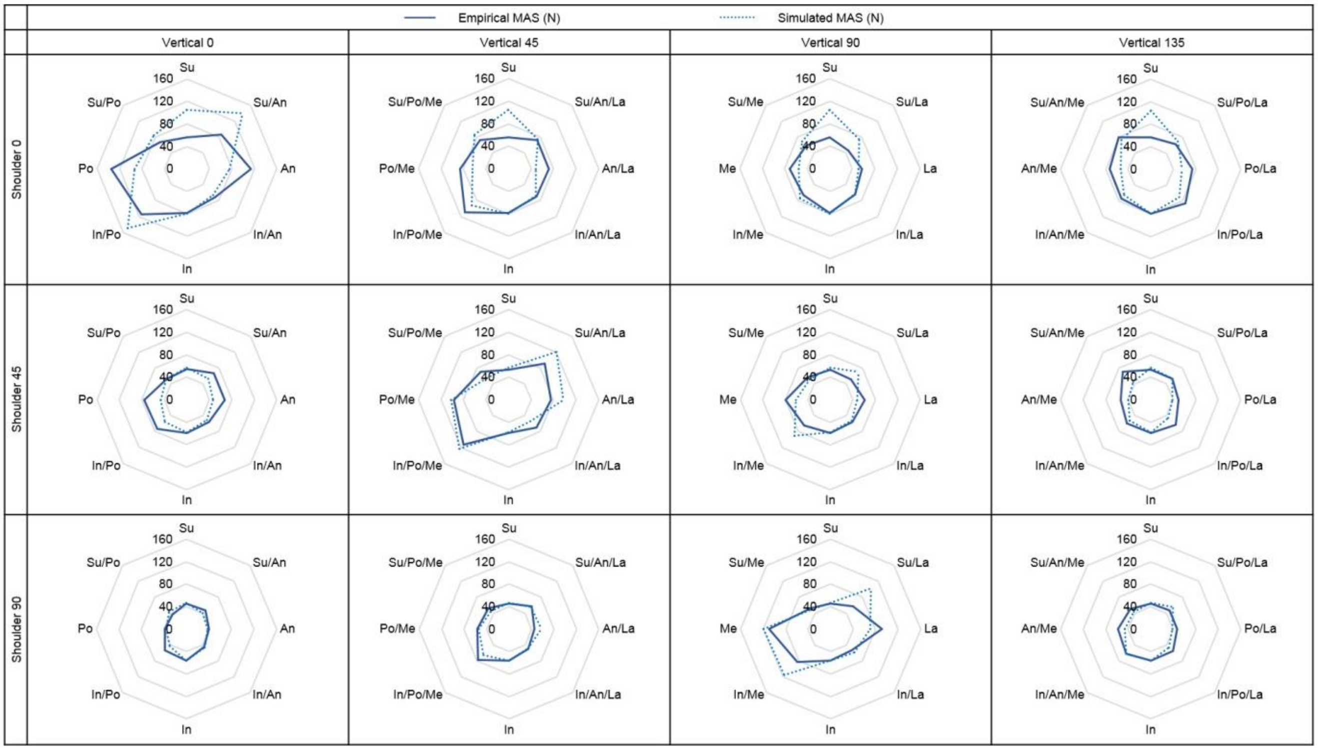


Figure 5: Radar charts showing the empirical and simulated MAS (N) at the shoulder hand locations using the convention from Figure 4.

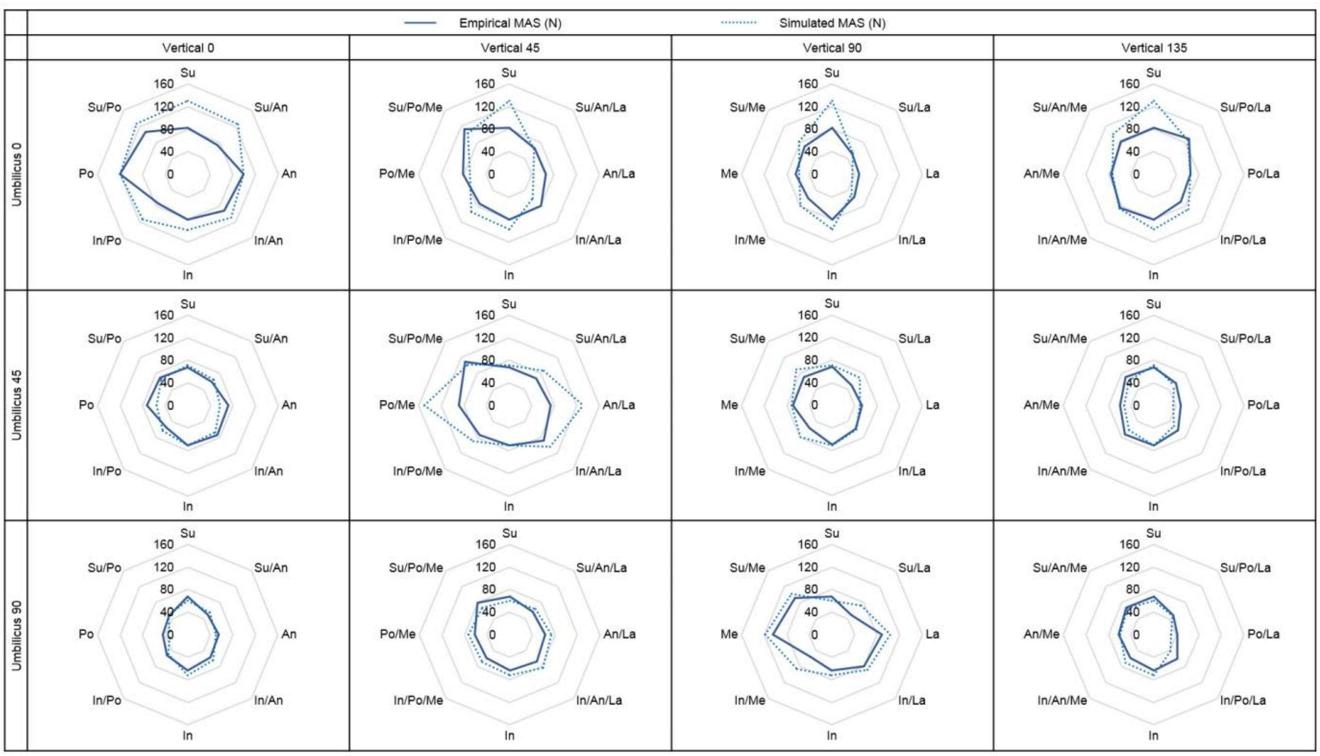


Figure 6: Radar charts showing the empirical and simulated MAS (N) at the umbilicus hand locations using the convention from Figure 4.

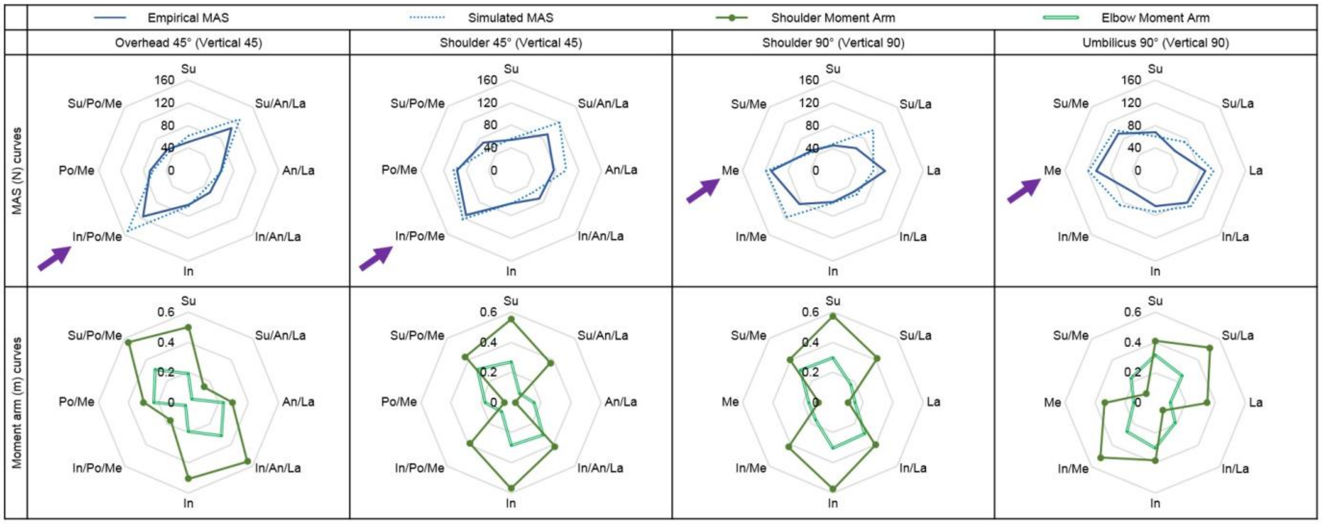


Figure 7: Radar charts showing selected empirical and simulated MAS (N) curves (from figures 3, 4, and 5) containing the strongest exertion direction (indicated by the arrow) at hand locations where the maximum empirical MAS direction coincides with that of the simulated MAS. The bottom row plots the moment arms (m) of the force vectors to the shoulder and the elbow corresponding to the selected MAS curves.

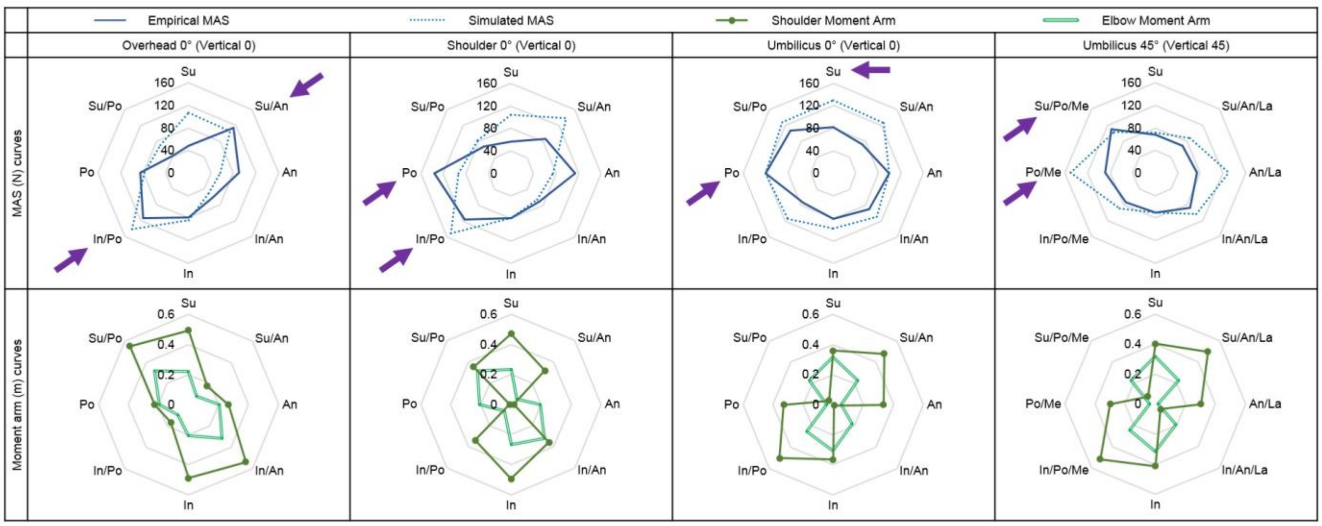


Figure 8: Radar charts showing selected empirical and simulated MAS (N) curves (from figures 3, 4, and 5) containing the strongest exertion directions (indicated by the arrows) at hand locations where the maximum empirical MAS direction does not coincide with that of the simulated MAS. The bottom row plots the moment arms (m) of the force vectors to the shoulder and the elbow corresponding to the selected MAS curves.

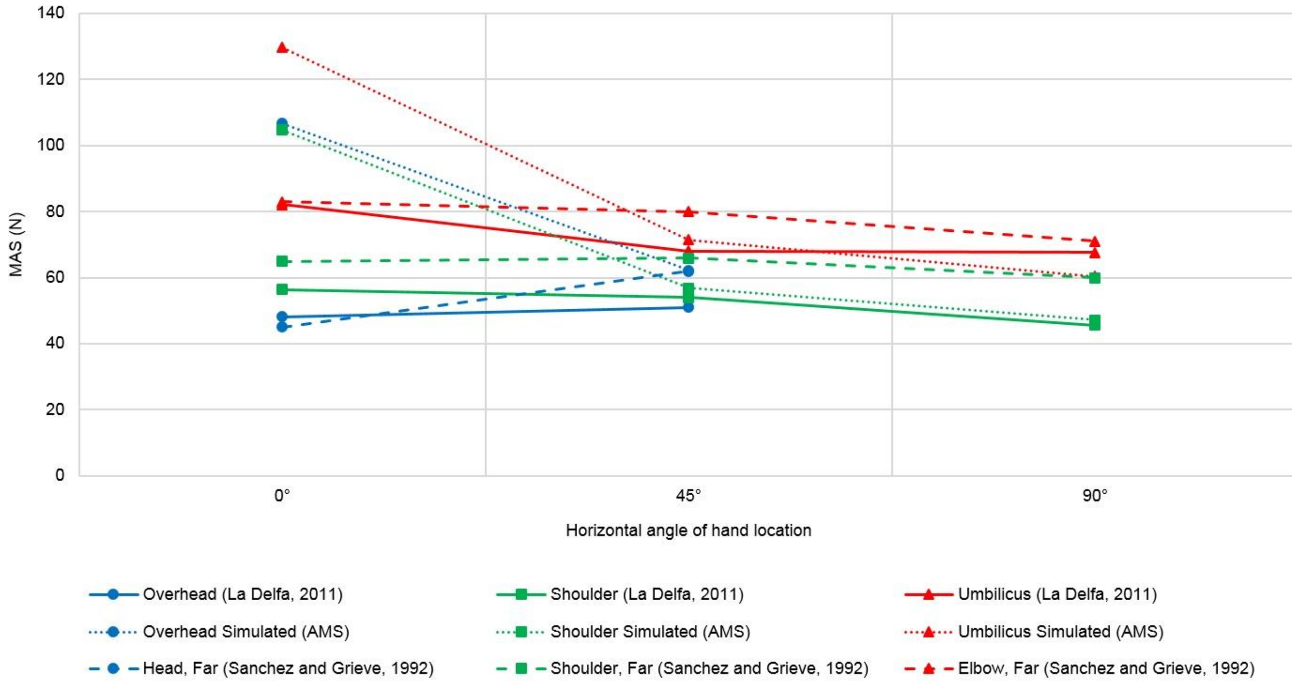


Figure 9: Comparison of empirical and simulated MAS (N) in the superior direction at all the hand locations. MAS data at the closest hand locations from Sanchez and Grieve (1992) are also included.