Journal of Biomechanics 163 (2024) 111952

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech

Short communication

Glenohumeral joint force prediction with deep learning

Pezhman Eghbali [a], Fabio Becce [b], Patrick Goetti [c], Philippe Büchler [d], Dominique P. Pioletti [a], Alexandre Terrier [a,c,*]

[a] Laboratory of Biomechanical Orthopedics, Ecole Polytechnique Fédérale de Lausanne, Institute of Bioengineering, Switzerland
[b] Department of Diagnostic and Interventional Radiology, Lausanne University Hospital and University of Lausanne, Switzerland
[c] Department of Orthopedics and Traumatology, Lausanne University Hospital and University of Lausanne, Switzerland
[d] ARTORG Center for Biomedical Engineering Research, University of Bern, Switzerland

ARTICLE INFO

Keywords:
Glenohumeral joint force
Deep learning
Musculoskeletal model

ABSTRACT

Deep learning models (DLM) are efficient replacements for computationally intensive optimization techniques. Musculoskeletal models (MSM) typically involve resource-intensive optimization processes for determining joint and muscle forces. Consequently, DLM could predict MSM results and reduce computational costs. Within the total shoulder arthroplasty (TSA) domain, the glenohumeral joint force represents a critical MSM outcome as it can influence joint function, joint stability, and implant durability. Here, we aimed to employ deep learning techniques to predict both the magnitude and direction of the glenohumeral joint force. To achieve this, 959 virtual subjects were generated using the Markov-Chain Monte-Carlo method, providing patient-specific parameters from an existing clinical registry. A DLM was constructed to predict the glenohumeral joint force components within the scapula coordinate system for the generated subjects with a coefficient of determination of 0.97, 0.98, and 0.98 for the three components of the glenohumeral joint force. The corresponding mean absolute errors were 11.1, 12.2, and 15.0 N, which were about 2% of the maximum glenohumeral joint force. In conclusion, DLM maintains a comparable level of reliability in glenohumeral joint force estimation with MSM, while drastically reducing the computational costs.

1. Introduction

The glenohumeral (GH) joint force refers to the force exerted by the humerus on the glenoid fossa (Pataky et al., 2021). Although direct in vivo measurement of this force is not feasible, except with instrumented prostheses (Bergmann et al., 2011), computational musculoskeletal models (MSM) enable its prediction (Sarshari et al., 2021a). However, employing the MSM model directly for subject-specific shoulder modeling can be computationally demanding (Rane et al., 2019). To address this challenge, deep learning presents a viable solution (De Vries et al., 2016; Wang et al., 2020; Burton II et al., 2021). The computational burden associated with subject-specific shoulder modeling using the MSM model can be alleviated by leveraging deep learning techniques.

Deep learning models (DLM) can learn data representations with multiple abstraction levels (LeCun et al., 2015). These models have been utilized in numerous prediction problems with impressive performance. In the scope of musculoskeletal dynamics prediction, several studies have been conducted. Wang et al. (2020) used fully-connected neural networks (FCNN) and XGBoost to predict the knee adduction moment during walking with data collected from two low-cost wearable sensors. Burton II et al. (2021) performed prediction of lower extremity muscle and joint contact forces of total knee replacement patients from joint kinematics, ground reaction forces, and anthropometrics during four different activities of daily living with recurrent neural networks, convolutional neural networks, and FCNN. Zhang et al. (2022) predicted the joint angle and muscle forces at the knee joint during different walking speeds, and at the wrist joint during wrist flexion/extension, from the electromyography (EMG) data with physics-informed FCNN. Giarmatzis et al. (2020) developed FCNN and support vector machines to predict all components of medial and lateral knee contact forces during different gait speeds based on optical motion capture. Other studies performed prediction of elbow torques and limb movements from EMG data with convolutional and recurrent neural networks (Song and Tong, 2005; Xia et al., 2018), prediction of muscle lengths and moment arms based on joint angles generated from an arm and hand model using FCNN (Smirnov et al., 2021), prediction of internal muscle forces based on kinetic, kinematic, and EMG measurements with FCNN (Rane et al., 2019). These models' inputs were kinematics or EMG data. A fast and easy evaluation of the MSM results without needing motion data for every subject would be preferable for researchers performing patient-specific finite element analysis.

* Correspondence to: EPFL-LBO, Station 9, 1015 Lausanne, Switzerland.
E-mail address: alexandre.terrier@epfl.ch (A. Terrier).

https://doi.org/10.1016/j.jbiomech.2024.111952
Accepted 11 January 2024
Available online 12 January 2024
0021-9290/

Table 1
Number of generated virtual subjects by implant type and sex.

Implant/Sex	Female	Male
Anatomical	251	233
Reverse	243	232

Therefore, we aimed to predict patient-specific glenohumeral joint force (the reaction force on the glenoid) with a DLM, using training data provided by an upper-limb patient-specific MSM, and generated subjects from an existing clinical registry. Several anatomical features and surgical options were considered, with the final objective to facilitate TSA patient-specific finite element modeling.

2. Methods

2.1. Data

We generated 959 virtual subjects (Table 1) from an upper-limb musculoskeletal model (Sarshari et al., 2021a). For each virtual subject, we considered sex, height, weight, glenoid version, glenoid inclination, and the physiological cross-sectional area (CSA) of the four rotator cuff muscles: supraspinatus (SS), infraspinatus (IS), subscapularis (SC), and teres minor (TM). These anatomical features were considered for both anatomical and reversed TSA. We simulated three activities: abduction in the scapular plane, abduction in the scapular plane with a mass of 2 kg in hand, and abduction in the frontal plane with a mass of 2 kg in hand. Based on these inputs, the MSM calculated the upper-limb muscles and glenohumeral joint force as a time series associated with activity time. We considered the following abduction angles: 30, 40, 50, 60, 70, 80, 90, and 100 degrees. The abduction activities simulated by the MSM were based on recorded motion and EMG data (Sarshari et al., 2021b), and scaled based on patient-specific parameters (Sarshari et al., 2021a).

The virtual subjects were generated by the Metropolis Monte-Carlo Markov Chain (MCMC) algorithm (Geyer, 2011). We replicated four groups of subjects: males with anatomical TSA, females with anatomical TSA, males with reversed TSA, and females with reversed TSA (Table 1). Samples were generated by MCMC for each of these groups, for all parameters mentioned above, from their distributions based on an existing clinical registry (Fig. A1–A9 in the supplementary data). This clinical registry consisted of preoperative and postoperative clinical data and computed tomography (CT) scan images of patients who underwent anatomical or reversed TSA (Mariaux et al., 2021). We used CT scans to calculate the glenoid version, the glenoid inclination, and the CSA of the rotator cuff.

2.2. Deep learning model optimization

The mentioned 12 features were the input and the components (x, y, z) of the glenohumeral joint force were the output of the model. We optimized the hyperparameters of the DLM, which was a fully-connected neural network, with Bayesian optimization provided by Keras-tuner (O'Malley et al., 2019). We explored the considered hyperparameters search space for 100 iterations (Table 2). This search space consisted of the following range of variables: from 2 to 10 hidden layers with a step of one, from 20 to 250 neurons with a step of 10, two possible activation functions (Exponential Linear Units (ELU), and rectified linear unit (ReLU)), whether or not to use dropout and if yes a rate between 0.05 to 0.5, three possible optimizers (Adam, Nadam and stochastic gradient descent (SGD)). For Adam and Nadam, an initial learning rate between 1e-5 and 1e-2 was considered, while an exponential learning rate schedule was used for SGD (Table 2). The output layer included three neurons for the three glenohumeral joint force components (GHFx, GHFy, and GHFz) in the scapula coordinate system (Terrier et al., 2014): *x* for postero-anterior, *y* for infero-superior, and z for medio-lateral (right scapula). We evaluated the model using the coefficient of determination and the mean absolute error of the glenohumeral joint force components and magnitudes as well as the mean angular difference between the force vectors resulting from MSM and DLM. We also compared the computation time between MSM and DLM.

The training dataset included 85% of the whole data (815 cases) and the remaining 15% (144 cases) was used as the test dataset for the final evaluation of the model. Besides, 15% of the training dataset (122 cases) was used for validation, to optimize the hyperparameters. The models were developed with the TensorFlow library 2.12.0 (Abadi et al., 2015) in Python 3.10 (Van Rossum and Drake, 2009). The choice of 815 cases for training was justified by the evaluation of the generalization performance of the model (A10 in the supplementary data).

The virtual patients dataset, DLM Python code, and simulation results are available at c4science.ch/diffusion/DLMMSM/. The MSM is available at c4science.ch/source/msm_ul/.

3. Results

The optimized DLM consisted of 7 hidden layers, with 250, 20, 250, 160, 90, 90, and 100 neurons, respectively. Each layer was followed by a dropout layer with a 0.05 rate and a batch normalization layer. The activation function of each hidden layer was ELU. The optimizer was Adam with an initial learning rate of 1e-5 (Fig. 1, Table 2).

The coefficients of determination for the prediction of the three components and the magnitude of the glenohumeral joint force, GHFx, GHFy, GHFz, and GHFm were 0.97, 0.98, 0.98, and 0.97 (Fig. 2). The corresponding mean absolute errors were 11.1, 12.2, 15.0, and 17.9 N, about 2% of the maximum glenohumeral joint force (approximately 800 N). These results were averaged for all abduction angles: 30, 40, 50, 60, 70, 80, 90, and 100 degrees (Fig. 3). The mean difference between the MSM and DLM resultant force vector direction was 3.4 degrees.

We also evaluated the model on the abduction angles not presented in the training dataset: 25, 35, 45, 55, 65, 75, 85, 95, and 105 degrees. The GHFx, GHFy, GHFz, and GHFm coefficients of determination, averaged for all abduction angles, were 0.97, 0.98, 0.98, and 0.97, and mean absolute errors were 11.7, 12.9, 16.1, and 18.5 N (Figure A11).

The computation time of the glenohumeral joint force was less than one second in DLM, while it took 30 to 45 min with the MSM on a standard workstation.

4. Discussion

This study aimed to test the possibility of getting the glenohumeral joint force prediction of an MSM by a DLM. We successfully obtained an optimized DLM providing predictions with a mean absolute error below 15.0 N for all components of the force, which is acceptable compared to the overall uncertainty of MSM predictions (Menze et al., 2023). The main advantage of the DLM over the MSM is the much lower required computation time: less than 1 s vs 30–45 min on a regular workstation. Besides, it would be much easier to integrate the DLM within a larger workflow, including finite element simulations, statistical modeling, and preoperative planning for TSA. The method provided here could be easily extended to other joint and muscle force predictions.

The reliability of our DLM was acceptable compared to other DLMs for MSM parameter prediction. A neural network was developed to map

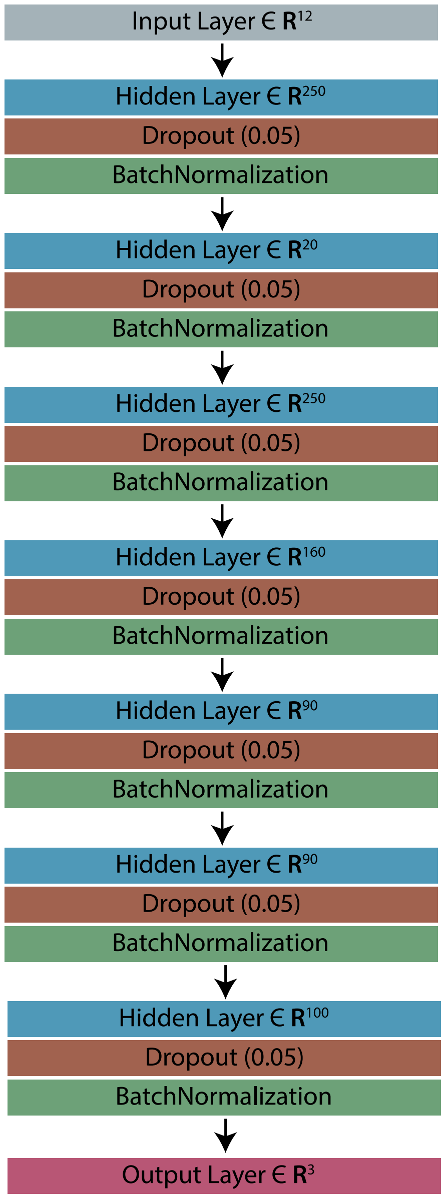

Fig. 1. DLM architecture; input layer with 12 features, 7 hidden layers with 250, 20, 250, 160, 90, 90, and 100 neurons, respectively, followed by a Dropout layer with a 0.05 rate and a batch normalization layer, and an output layer with 3 neurons for the components of the glenohumeral joint force.

kinematics and shoulder muscle EMG, recorded for one subject, to the glenohumeral joint reaction force (De Vries et al., 2016). They reported 0.83–0.98 intraclass correlation coefficients between the MSMs and the neural network's joint reaction force time series for different shoulder activities. The MSM employed in their study was the Delft Shoulder and Elbow Model, DSEM (Van der Helm, 1994). Sharma et al. (2022) developed machine learning models for predicting different upper-limbs MSM (www.anybodytech.com) results based on motion data, recorded from five subjects. They evaluated linear models and neural networks and reported a minimum of 23% of normalized (based on the MSM predictions) RMSE for different joint reaction forces. Mubarrat and Chowdhury (2023) developed a convolutional long short-term memory (LSTM) model to predict shoulder joint reaction forces based on motion data for eight participants. They reported a mean of 18.6% normalized RMSE for medial-lateral, 19.2% for inferior–superior, and 21.3% for anterior–posterior force for their best model. Their ground truth resulted from AnyBody software. These three studies had fundamental differences from ours. In the first study (De Vries et al., 2016), the input data comprised 3D kinematics and EMG signals captured during random upper extremity movements and active daily living tasks (e.g., brushing teeth). For the second study (Sharma et al., 2022), the input was motion data for the Reach-to-Grasp task in the forward direction executed at a self-selected pace. In the third study (Mubarrat and Chowdhury, 2023), the input consisted of 3D shoulder kinematics data collected across 30 different shoulder activities. However, in our case, the input was MSM results for three shoulder abductions. Moreover, their input was recorded data for every patient, while the MSM we used scaled recorded data for one subject based on patient-specific parameters (Sarshari et al., 2021a,b). The models of De Vries et al. (2016) and Mubarrat and Chowdhury (2023) predicted the time course of the glenohumeral joint force, and the model of Sharma et al. (2022) predicted the time course of different MSM outcomes (e.g., joint angles and forces, muscle forces, and activations). The prediction of our model was the glenohumeral joint force for a specific elevation angle, but although the model was only trained on some elevation angles, it could make predictions for any elevation angle (Fi. A11 in the supplementary data).

The main limitation of the present DLM is the restricted number of activities considered. We indeed replicated the elevation movements in two different planes. However, this was a reasonable choice for this methodology study. Besides, we may restrict these simple movements for future potential applications in design testing of preoperative planning. We assume that the method presented here could be easily and successfully applied to the other movements implemented in the used MSM (Sarshari et al., 2021a). This model is restricted to the prediction of glenohumeral joint force for one of the three activities in the training dataset. An alternative would have been to train the model with a set of joint angles, which would have allowed prediction for any combination of joint angles representing other activities. However, for practical reasons, we intentionally restricted the model to three important movements in order to obtain a reasonable prediction of typical glenohumeral forces without requiring kinematics data as input. The present model could be extended by assigning joint angles to the joint forces independently of activity, but in this case, we would require kinematic measurements as input. Since the present model does not require motion capture, it offers the advantage of a fast and simple estimation of the glenohumeral joint force, which can be

Table 2
DLM hyperparameters' range of and optimized values.

Hyperparameter	Range	Optimized value
Number of hidden layers	[2, 10] with step = 1	7
Number of units in each hidden layer	[20, 250] with step = 10	[250, 20, 250, 160, 90, 90, 100]
Activation function	[ReLU, ELU]	ELU
Dropout	[True, False]	True
Dropout rate	[0.05, 0.5]	0.05
Optimizer	[Adam, Nadam, SGD]	Adam
Adam and Nadam optimizer learning rate (lr)	[1e−05, 1e−02]	1e−05
SGD exponential decay (lr) schedule initial (lr)	[1e−05, 1e−02]	–
SGD exponential decay (lr) schedule decay rate	[0.5, 0.99]	–

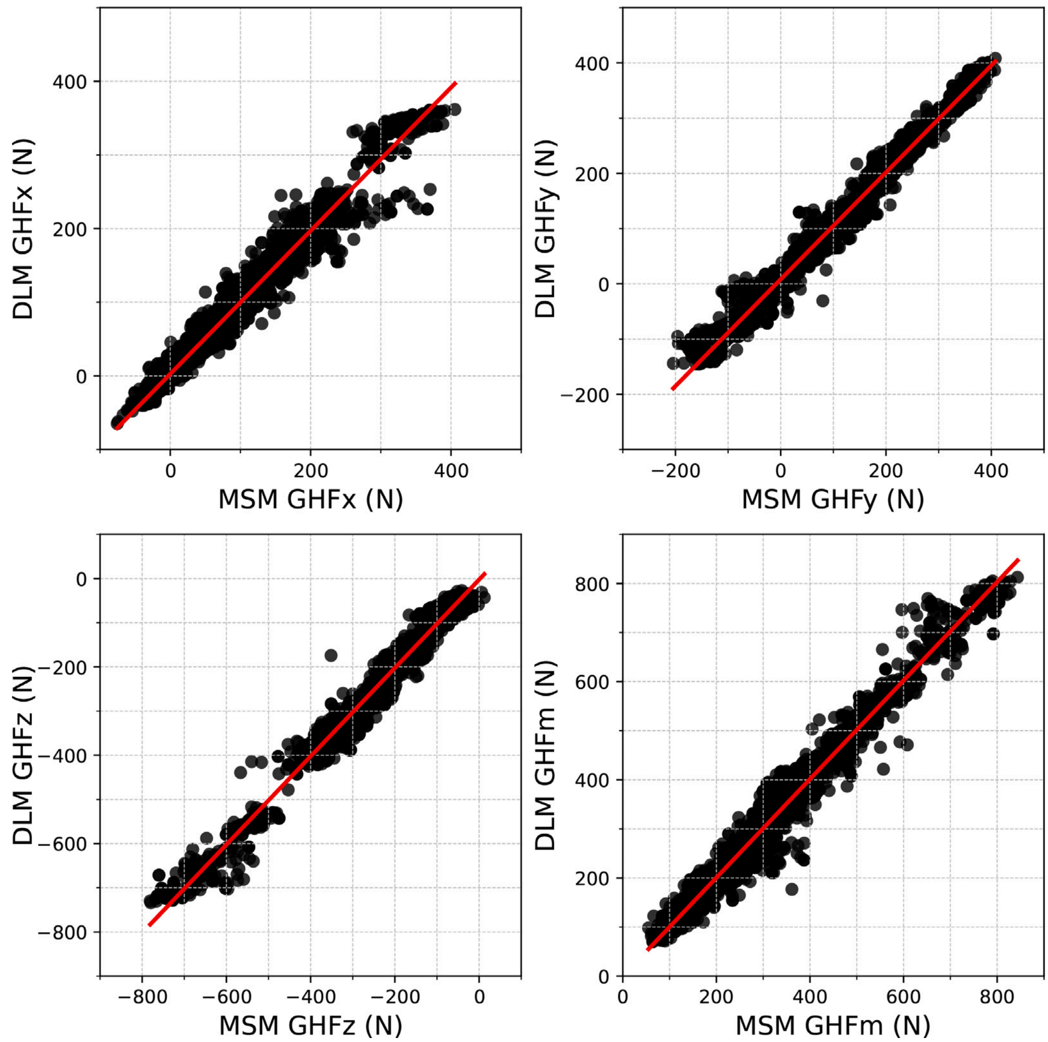

Fig. 2. Correlation between the MSM and DLM values of the components (GHFx, GHFy, GHFz, GHFm) and the magnitude (GHFm) of the glenohumeral joint force at different abduction angles: 30, 40, 50, 60, 70, 80, 90, 100 degrees. The average coefficients of determination were 0.97, 0.98, 0.98, and 0.97 for GHFx, GHFy, GHFz, and GHFm, respectively.

used, for example, in finite element modeling of the glenoid bone. As a secondary limitation, compared to the model of De Vries et al. (2016) and Mubarrat and Chowdhury (2023), we may report the fixed angles of elevation, instead of the full range of motion. However, as we focused on a simple elevation movement, this choice was more straightforward and more rational, especially for interpreting the resulting output. The interval of 10 degrees of elevation between each prediction was also sufficient to report the force variation. Anyway, for more complex movements, where the elevation angle could not be used as a pseudo-time parameter, the same method could be applied using, for example, discrete values of the percentage of the movement cycle as a pseudo-time parameter. Still, our choice of fixed and limited pseudo-time points holds value in the rapid estimation of the glenohumeral joint force for daily living activities, which can benefit patient-specific shoulder modeling or preoperative planning software. In this context, considering selected angles during abduction appears to be a reasonable choice. The third limitation concerned using motion data, captured from one subject and scaled for virtual subjects. Although this cannot be as accurate as capturing motion data for all subjects, it is the more feasible approach as capturing motion data for hundreds of subjects would be much more expensive and laborious and, to our knowledge, has not yet been reported in the literature.

Deep learning has the potential to offer a faster estimation of the glenohumeral joint force compared to MSM while maintaining comparable reliability. This can considerably simplify the patient-specific prediction of glenohumeral joint force so that it can be used with finite element analysis to test the design of glenoid implants or to test surgical techniques. By leveraging deep learning techniques, computational efficiency can be improved without sacrificing the reliability of the force estimation. Consequently, deep learning provides a promising avenue for advancing patient-specific shoulder analysis such as automating the patient-specific modeling workflow and applying it to large cohorts of patients.

CRediT authorship contribution statement

Pezhman Eghbali: Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Fabio Becce:** Writing – review & editing, Supervision, Funding acquisition, Data curation. **Patrick Goetti:** Writing – review & editing,Supervision, Data curation. **Philippe Büchler:** Writing – review & editing, Supervision, Funding acquisition. **Dominique P. Pioletti:** Writing – review & editing, Supervision. **Alexandre Terrier:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

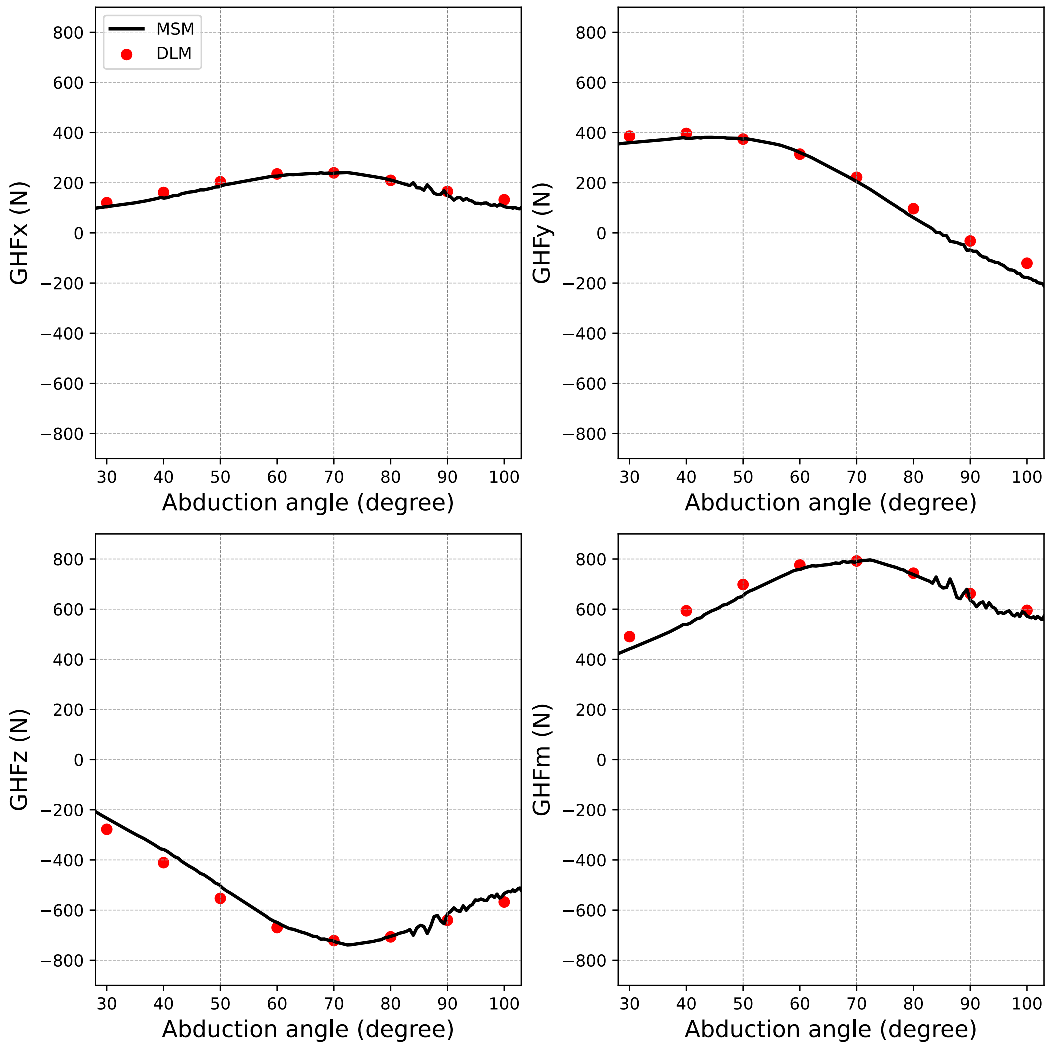

Fig. 3. Glenohumeral joint force components (GHFx, GHFy, GHFz) and magnitude (GHFm) vs. abduction angle predicted by the MSM (curve) and DLM (red points). This virtual subject was a male, 85.0 kg, 175 cm, having −2.0 degrees of glenoid (retro)version, 6.0 degrees of glenoid inclination, a CSA of 5.5, 7.0, 12.0, and 2.5 cm^2 for the SS, IS, SC, and TM, respectively, with an anatomical TSA implant, and performing an abduction in the scapular plane with 2 kg in hand. We presented this virtual subject as his parameters represented the average values of the generated parameters' distributions by MCMC (Fig. A2–A9).

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was supported by the Swiss National Science Foundation (SNF 189972) and the "Lausanne Orthopedic Research Foundation" (LORF).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbiomech.2024.111952.

References

Abadi, M., et al., 2015. TensorFlow: Large-scale machine learning on heterogeneous systems. URL https://www.tensorflow.org/. Software available from tensorflow.org.
Bergmann, G., et al., 2011. In vivo gleno-humeral joint loads during forward flexion and abduction. J. Biomech. 44 (8), 1543–1552.
Burton II, W.S., Myers, C.A., Rullkoetter, P.J., 2021. Machine learning for rapid estimation of lower extremity muscle and joint loading during activities of daily living. J. Biomech. 123, 110439.
De Vries, W., et al., 2016. Can shoulder joint reaction forces be estimated by neural networks? J. Biomech. 49 (1), 73–79.
Geyer, C.J., 2011. Introduction to Markov chain monte Carlo. In: Handbook of Markov Chain Monte Carlo, vol. 20116022, Boca Raton, p. 45.
Giarmatzis, G., Zacharaki, E.I., Moustakas, K., 2020. Real-time prediction of joint forces by motion capture and machine learning. Sensors 20 (23), 6933.
LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. nature 521 (7553), 436–444.
Mariaux, S., et al., 2021. Is preoperative glenoid bone mineral density associated with aseptic glenoid implant loosening in anatomic total shoulder arthroplasty? BMC Musculoskelet. Disord. 22, 1–9.
Menze, J., et al., 2023. The effect of pathological shoulder rhythm on muscle and joint forces after reverse shoulder arthroplasty, a numerical analysis. Clin. Biomech. 106030.
Mubarrat, S., Chowdhury, S., 2023. Convolutional LSTM: A deep learning approach to predict shoulder joint reaction forces. Comput. Methods Biomech. Biomed. Eng. 26 (1), 65–77.
O'Malley, T., et al., 2019. KerasTuner. https://github.com/keras-team/keras-tuner.
Pataky, J., et al., 2021. Glenohumeral joint loading is impacted by rotator cuff tear severity during functional task performance. Clin. Biomech. 90, 105494.
Rane, L., et al., 2019. Deep learning for musculoskeletal force prediction. Ann. Biomed. Eng. 47, 778–789.

Sarshari, E., Mancuso, M., et al., 2021b. Muscle co-contraction in an upper limb musculoskeletal model: EMG-assisted vs. standard load-sharing. Comput. Methods Biomech. Biomed. Eng. 24 (2), 137–150.

Sarshari, E., et al., 2021a. A Matlab toolbox for scaled-generic modeling of shoulder and elbow. Sci. Rep. 11 (1), 20806.

Sharma, R., et al., 2022. Machine learning for musculoskeletal modeling of upper extremity. IEEE Sens. J. 22 (19), 18684–18697.

Smirnov, Y., et al., 2021. Solving musculoskeletal biomechanics with machine learning. PeerJ Comput. Sci. 7, e663.

Song, R., Tong, K.-Y., 2005. Using recurrent artificial neural network model to estimate voluntary elbow torque in dynamic situations. Med. Biol. Eng. Comput. 43, 473–480.

Terrier, A., et al., 2014. Measurements of three-dimensional glenoid erosion when planning the prosthetic replacement of osteoarthritic shoulders. Bone Joint J. 96 (4), 513–518.

Van der Helm, F.C., 1994. A finite element musculoskeletal model of the shoulder mechanism. J. Biomech. 27 (5), 551–569.

Van Rossum, G., Drake, F.L., 2009. Python 3 Reference Manual. CreateSpace, Scotts Valley, CA, ISBN: 1441412697.

Wang, C., et al., 2020. Real-time estimation of knee adduction moment for gait retraining in patients with knee osteoarthritis. IEEE Trans. Neural Syst. Rehabil. Eng. 28 (4), 888–894.

Xia, P., Hu, J., Peng, Y., 2018. EMG-based estimation of limb movement using deep learning with recurrent convolutional neural networks. Artif. Organs 42 (5), E67–E77.

Zhang, J., et al., 2022. Physics-informed deep learning for musculoskeletal modelling: Predicting muscle forces and joint kinematics from surface EMG. IEEE Trans. Neural Syst. Rehabil. Eng..