JCPR Journal of Clinical Physiotherapy Research Original Article

Estimation of Spinal Loads across Biomechanical Models, Using the Practical Approach of Artificial Neural Network for Posture Prediction

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Submitted: 2019-01-23; **Accepted**: 2019-03-18; ***DOI:*** 10.22037/jcpr.v4i2.31102

Abstract

Introduction: Workers usually perform lifting and reaching tasks as a part of their daily job. Having a proper posture plays a key role for reduction of the loads applied to the spine during lifting, and as a result, prevention of further injuries. We aimed to extend a previously published work on the spinal load estimation which utilized the different biomechanical tools by the artificial neural network (ANN) for a posture prediction instead of the marker-based motion capture during lifting and reaching activities. **Method and Materials**: : In this study, to underline the efficacy of biomechanical models, we examined and compared the results of multiple mathematical tools (loads at L4-L5 and L5-S1 levels) for reach-and-lift tasks in the sagittal plane (i.e., symmetric tasks) and for lifting tasks with 30° and $60^{\circ}$of back rotation (i.e., asymmetric tasks). In this regard, we employed AnyBody, OpenSim and 3DSSPP as modeling softwares), a regression equation called Arjmand equation, and finally, McGill, Potvin, and Merryweather as estimators. Inputs to these models were provided using an ANN, a posture prediction model introduced by literature for predicting the three-dimensional posture of the spine in various activities, which is trained and tested by experimental data. **Results**: Results showed that although the AnyBody software has the most accurate approximations, the Arjmand equation also offers a quite realistic output that considering its simplicity, it is compatible with the biomechanical nature of the problem. Using the ANN posture prediction, the results (for 4 symmetric tasks) showed less than 15% error than a marker-based study in the literature which was considered as an accurate model. **Conclusion**: Arjmand regression along with ANN for the posture prediction may provide a reliable solution to estimate spinal loads during lifting and reaching activities,, especially when an equipped laboratory or/and expensive software licenses are not available.

Keywords: Artificial Neural Network, Spine biomechanics, AnyBody, OpenSim

Please cite this paper as: Shokouhyan SM, Davoudi M, Nikzad Goltapeh A, Parnianpour M. Estimation of Spinal Loads across Biomechanical Models, Using the Practical Approach of Artificial Neural Network for Posture Prediction. J Clin Physio Res. 2019; 4(2): e13. *DOI*: 10.22037/jcpr.v4i2.31102

Introduction

Lower back injuries are deemed as pain-inducing and crippling conditions at working and industrial environments which impose [1] a considerable financial and psychological impact to patients and societies . Though it has not been completely understood why such disorders are so prevalent, lifting activities are considered as an independent risk factor in literature [2]. Repeating a demanding task (for instance, daily workers carrying harvest in farms), higher magnitude of loads, and inappropriate lifting or reaching postures during work usually lead to back injuries [3]. While, for symmetric tasks, compression forces on the spine cause the damage, for activities involving asymmetric lifting tasks, shear forces inflict the pain upon patients [4]. Asymmetric loading increases the level of muscular activities and maximizes muscular engagements, thereby imposing higher risk factors on the spine and vertebrae [5].

Despite being more difficult than other methods, in vivo measurements are the most precise method for determining shear and compression forces on the spine[6]. In recent decades, a variety of intuitive biomechanical models, ranging from a simplistic 2-dimensional model with one or two equivalent back muscles [7] to open-source software's [8] and commercial ones [9], have been introduced to estimate the spinal loads during different activities, mainly forces exerted on L5-S1 and L4-L5 discs. These models generally offer three different analytical models: static, quasi-static, and dynamic [10]. During the static analysis, models solve biomechanical equations for a fixed posture. In contrast, the dynamic analysis takes motions of the joints into account, and calculates the velocity and acceleration

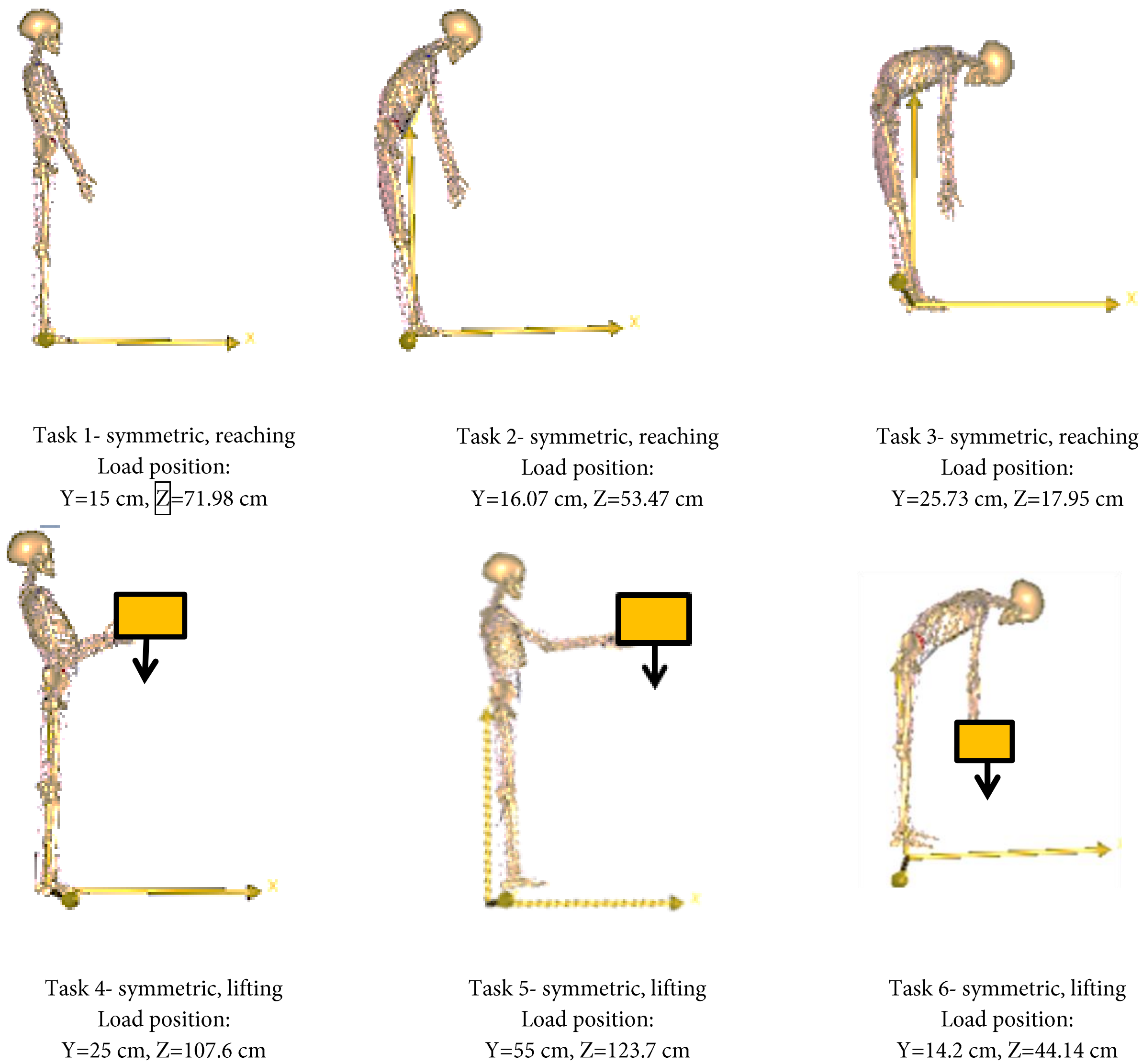

Figure 1. Schematics of symmetric reaching and lifting at sagittal plane (tasks 1 to 6.). Note that Y is the horizontal distance from the body, and Z is the vertical distance from the ground

of each segment. The quasi-static analysis also means that a specific movement is divided into multiple static postures, and the velocity and acceleration are set equal to zero throughout the entire analysis. To estimate whether it is safe to perform an activity, one can compare the results from these modeling tools with the estimated tolerance levels of spinal structures reported in the literature. For instance, the National Institute for Occupational Safety and Health (NIOSH) lifting guide is a well-known criterion in which a range of 3400N to 6400N is set as the permissible force levels for spinal discs [11]. According to this guideline, when forces exceed 3400N, the risk of endplate microfracture and degeneration on the discs increase.

Along with magnitude and placement of hand load, the body posture plays a crucial role in approximating the shear and compressive loads on the spine. Rajaee et al. [12] acquired postures of 26 various activities in an individual using the motion caption method and fed these data as inputs to several available biomechanical models. Forces estimated at L5-S1 and L4-L5 levels were compared with each other, and higher accuracy of results of AnyBody model, as opposed to other methods, was reported. Along with in-vivo motion capture approaches at laboratories, in the literature, two other methods have been employed to approximate the body posture with less accurate results. These methods do not have a limitations of in vivo methods. The first method is to evaluate body posture using the inverse kinematics and optimization [13]. In this method, the indeterminate equations are solved by forcing multiple constraints on biomechanical equations and searching for solutions in such a way that the desired body posture is reached. For instance, moment at L5-S1 level can be minimized for a lifting activity with a constant hand load, and joint locations can be found via the optimization techniques. The other alternative is to use artificial neural network (ANNs), which can predict the spine posture and exerted forces [14]. In a study carried out by Gholipour and Arjmand [14], ANNs were trained and tested using the direct measurements of the spinal postures (measured by IMU sensors) for 40 healthy subjects in various reaching and lifting activities with an average error of fewer than eleven degrees. This paper aimed to develop the results of Rajaee [12]. We implemented the ANN models introduced by Gholipour and Arjmand [14] to simulate various body postures for reaching and lifting tasks. We used these data as inputs to seven biomechanical models, and eventually, we compared the estimated shear and compressive forces at L5-S1 and L4-L5 discs to determine their accuracy. Despite having errors for the prediction of the body posture, these easy-to-calculate models facilitate the estimation of spinal forces and their associated risk factors for symmetric and asymmetric activities.

Material and Methods

Simulated Tasks

Sixteen static activities in the upright and flexed positions during symmetric and asymmetric loads and postures were investigated in this study. T1, T12 and S1 rotations were determined by the ANN [14]. The inputs to this model are the body height and the position of the hand load, and the outputs consist of nine Eulerian rotations of T1, T12, and S1 segments. We assumed an identical bodyweight of 74 kg and height of 178cm during the entire simulation to represent a healthy male subject while holding a load of 19.8 kg. These included nine reaching (zero load) and seven lifting activities listed in Table 1. The second column of the Table indicates the symmetry wherein θ equals rotation of the spine around the longitudinal axis. Reaching (R) or lifting (L) is denoted in the third coloumn, and the distance of the load in the horizontal and vertical directions relative to the body and the ground is represented in the fourth and fifth columns, respectively. Fig.1 demonstrates the schematics of the tasks corresponding to the symmetric activities.

Table 1. Characteristics of simulated activities. θ denotes the angle of symmetry, and tasks with a value equal to zero means that tasks were performed at the sagittal plane. Y (cm) is the hand load horizontal distance from the body, and Z (cm) represents vertical distance of load from the ground

Task	Θ^0	Reaching Lifting	Box Position (m=19.8 Kg)	
			Y (Horizontal)	Z (Height)
1	0*	R	15	71.98
2	0*	R	16.7	53.47
3	0*	R	25.07	17.93
4	0*	L	25	107.6
5	0*	L	55	123.7
6	0*	L	14.2	44.14
7	30**	R	15	71.98
8	30**	R	16.7	53.47
9	30**	R	25.07	17.93
10	30**	L	25	107.6
11	30**	L	55	123.7
12	60**	R	15	71.98
13	60**	R	16.7	53.47
14	60**	R	25.07	17.93
15	60**	L	25	107.6
16	60**	L	55	123.7

* Symmetric
** Asymmetric

Analysis Tools

The goal of this paper was to compare predictions (compressive and anterior-posterior shear loads at the L4-L5 and L5-S1 disc levels) of seven numerical tools when apply to identical activities. By doing so, we can determine disparities in the approximated spinal loads and assess the accuracy of each tool by comparing forces with in vivo intradiscal pressure measurements measured by Wilke et al. *[6]* and spine forces computed by Rajaee et al *[12]*. The seven tools used in this study, require its input data, such as body posture, hand load position and its magnitude, and body weight and height to analyze a given task.

AnyBody Modelling System

AnyBody (AnyBody Technology A/S, Aalborg, Denmark) modeling system has a detailed musculoskeletal model of the whole body. Its trunk includes seven rigid segments (pelvis, five lumbar vertebrae, and thorax) and muscles which either have a straight line of action or take a nonlinear trajectory crossing several points [15]. The gravity force of the thorax is exerted at its mass center, while lumbar weight is distributed along its whole length. For any given simulation, muscle forces and vertebral forces are calculated by applying the moment equilibrium equation at all levels [9]. In this study, we employed the lifting model of AnyBody Managed Model Repository (AMMR) and the inverse dynamic method. Body postures (extracted from the ANN above), load magnitude and load positions were logged to this model as the inputs and L4-L5, and L5-S1 shear and compressive forces were recorded as the outputs.

OpenSim Modelling System

OpenSim is an open-source biomechanical modeling software founded and developed at Stanford University. It has been used extensively by scholars to study a variety of tasks like lifting activities *[16, 17]*, but is rarely recruited for reaching tasks. In this study, we only used OpenSim (v3.0) to analyze the reaching activities. In order to do so, we modified the default model gait 2354. First of all, the weight and the height were set equal to 74 kg and 178 cm, and the scaling was performed to match this model to our general one. We then adjusted the kinematic of joint angle files to reach the specific static postures similar to the ones resulted from the ANN. There is no marker data as input, so we had to change the joint angles directly. Moreover, no forces were applied on the hand (reaching activities), and the gravity force was the only external force. After a couple of the computational steps, shear and compressive forces at the L4-L5 and L5-S1 levels were determined using Joint Reaction Analysis. These steps were repeated for different reaching tasks.

Table 2. *Comparison of compressive forces at L4-L5 between this study and (12)*

Task	3DSSPP		AnyBody		Arjmand (Sym:2010, Asym:2012)		McGill (Polynomial)		OpenSim	Wilke
	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN	In vivo
1	404 (17.4)	344	404.3(13)	465	360.62(8.9)	396	1067.6(0.3)	1064	341	592
2	1707	-	1213	-	1668	-	1068	-	1474	1361
3	1719(7.7)	1596	1815.2(16.1)	1563	1876(9.6)	1711	1067.6(22.6)	1381	2040	2016
4	1158(2.2)	1132	1234.2(5.1)	1174	1117.7(15.7)	1327	1215.5(1.5)	1235	-	1260
5	2178(1.4)	2146	2508(10.5)	2268	2408.9(7.9)	2617	2006.5(2.4)	2058	-	2268
6	2896	-	3150	-	3275	-	1337	-	-	2898
7	763	-	840	-	504	-	1068	-	850	-
8	1812	-	1338	-	1730	-	1068	-	1789	-
9	1400	-	1370	-	1760	-	1318	-	-	-
10	2256	-	2043	-	2900	-	2241	-	-	-
11	2910	-	2772	-	3450	-	1470	-	-	-
12	1200	-	839	-	609	-	1068	-	1224	-
13	1827	-	1239	-	1790	-	1068	-	1521	-
14	1800	-	2058	-	1727	-	1427	-	-	-
15	2920	-	2919	-	2500	-	2492	-	-	-
16	2341	-	2492	-	3300	-	1616	-	-	-

Table 3. *Comparison of compressive forces at L5-S1 between this study and (12)*

Task	3DSSPP		AnyBody		Arjmand (Sym:2010, Asym:2012)		Merryweather (HCBCF)		Potvin (LSBM)	OpenSim
	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN (Error%)	Vicon	ANN (Error%)	ANN
1	275(15.12)	324	461(12.6)	528	407.7(2.9)	420	494(0)	494	440.6(1.5)	360
2	1869	-	1266	-	1771	-	1991	-	1849	1443
3	1946(10.9)	1754	1844.4(11.8)	1649	1986.9(13)	1743	2332.1(17)	1992	1804.2(5.7)	2016
4	1203(1.7)	1225	1331.6(4.9)	1269	985(16.4)	1179	1353.5(1.5)	1333	1479.5(1.2)	-
5	2256(0.5)	2243	2633.9(10)	2393	2161.4(10)	2405	2198.4(0.9)	2178	2609.1(0.3)	-
6	3201	-	3218	-	3498	-	3388	-	3050	-
7	708	-	901	-	849	-	-	-	-	849
8	1900	-	1395	-	1772	-	-	-	-	1772
9	1292	-	1477	-	1414	-	-	-	-	-
10	2095	-	2181	-	2538	-	-	-	-	-
11	3200	-	2710	-	3320	-	-	-	-	-
12	1071	-	898	-	1209	-	-	-	-	1209
13	1833	-	1281	-	1519	-	-	-	-	1519
14	589	-	2197	-	1390	-	-	-	-	-
15	465	-	3098	-	2210	-	-	-	-	-
16	2342	-	2532	-	3280	-		-	-	-

3DSSPP Analysis Tool

3DSSPP predicts static strength requirements for tasks. It was first developed at the University of Michigan. This program allows input to simulate the loads and the subject's postures. For the purpose of this study, we used this software to determine lower back shear and compressive forces at L5-S1 and L4-L5 levels. At L5-S1 level, forces were calculated as the sum of Erector Spinea/Rectus Abdominis, abdominal force, upper body weight above L5-S1, and hand load. However, at L4-L5 lumbar level, torso muscle (five on the left and five on the right side) areas, moment arms and contractile force directions were utilized, and shear and compressive forces were computed using the double optimization method *[18]*. Each activity needs its own input set such as body posture, hand load position, and subject's size to simulate a given task. Although 3DSSPP (14 days free trial) can predict the body posture for a given hand load placement, we used the ANN model for the posture prediction instead.

Table 4. *Comparison of shear forces at L4-L5 between this study and (12)*

Task	3DSSPP		AnyBody		Arjmand (Sym:2010,Asym:2012)		OpenSim
	ANN (Error %)	Vicon	ANN (Error %)	Vicon	ANN (Error %)	Vicon	ANN
1	135(2.1)	138	33(15.2)	39	7.8(39.6)	13	3
2	269	-	168	-	155	-	560
3	342(30.5)	262	240.3(15.5)	208	152.8(13.2)	135	1692
4	100(53)	213	108.7(0.25)	109	186.6(22.8)	242	-
5	121(23.4)	158	283.8(16.3)	244	501(9.7)	555	-
6	516	-	838	-	344	-	-
7	109	-	91	-	8	-	88
8	237	-	180	-	150	-	643
9	106	-	169	-	276	-	-
10	66	-	274	-	585	-	-
11	513	-	717	-	356	-	-
12	78	-	92	-	22	-	125
13	170	-	170	-	145	-	573
14	189	-	209	-	223	-	-
15	233	-	314	-	425	-	-
16	535	-	395	-	305	-	-

Table 5. Comparison of shear forces at L5-S1 between this study *and* **(12)**

Task	3DSSPP		AnyBody		Arjmand (Sym:2010,Asym:2012)		OpenSim
	ANN (Error %)	Vicon	ANN (Error %)	Vicon	ANN (Error %)	Vicon	ANN
1	220(0)	220	50.6(14.1)	59	127.5(8.2)	139	3
2	295	-	297	-	555	-	549
3	349(19.9)	291	519.2(43.4)	362	464.4(11.3)	524	1638
4	246(29.1)	347	209.2(2)	205	581.4(17.6)	706	-
5	304(11.1)	342	520.3(16.9)	445	1298.1(8.9)	1426	-
6	512	-	838	-	1009	-	-
7	227	-	173	-	177	-	83
8	300	-	330	-	520	-	624
9	271	-	210	-	866	-	-
10	255	-	328	-	1514	-	-
11	512	-	420	-	980	-	-
12	238	-	174	-	230	-	117
13	291	-	315	-	513	-	579
14	279	-	391	-	800	-	-
15	319	-	566	-	1220	-	-
16	539	-	680	-	876	-	-

Table 6. Mean errors of the spinal forces estimated from the ANN body postures compared to the forces resulted from the marker-based motion capture method for tasks 1,3,4 and 5 (these 4 tasks are the same as the tasks modeled in [12]) in Table 2 to Table 5

Force	3DSSPP	AnyBody	Arjmand regression model
Compression L4-L5	11.1%	7.1%	10.5%
Compression L5-S1	7%	9.82%	10.8%
Shear L4-L5	27.2%	11.8%	21.3%
Shear L5-S1	15%	19.1%	11.5%

Arjmand Regression Equation

This simple, and yet accurate predictive regression model, which implements a specific trunk finite element biomechanical model, can predict spinal compressive and shear loads based on its input variables for the static lifting activities *[19]*. In the case of symmetric lifting, the hand load anterior distance relative to the L5-S1, its magnitude, sagittal trunk flexion angle, and lumbopelvic (LP) ratio are model inputs *[19]*. For asymmetric activities *[20]*, the LP ratio is defined as the lumbar rotation divided by the pelvis rotation, where lumbar rotation is the difference of the relative angular position between trunk and pelvis for an activity. For symmetric and asymmetric activities performed one-handed or with two hands, the separate regression models are developed. As the lateral distance of load (Dy in Eq.1) should be considered zero for the symmetric tasks, in the present study, both symmetric and asymmetric tasks have been modeled using a regression model developed by Arjmand et al. in 2012 (Eq.1.) *[20]*.

$$\boldsymbol{C_{L5-S1} = b_0 + b_1T + b_2M + b_3Dx + b_4Dy + b_5T^2 + b_6M^2 + b_7(Dx)^2 + b_8(Dy)^2 + b_9T * M + b_{10}T * Dx + b_{11}T * Dy + b_{12}M * Dx + b_{13}M * Dy + b_{14}Dx * D} \quad \text{Eq.1}$$

where T, M, and Dx and Dy are in degree, kg, cm, and cm, respectively, and the spinal load (CL5-S1) is calculated in N.

Hand Calculation Back Compressive Force (HCBCF) Model

The HCBCF model (Merryweather et al. *[21]*) approximates the L5-S1 compressive force using a single-level (i.e., L5-S1) biomechanical model. This model regards the entire spine as a segment and includes only one single equivalent back muscle with a constant sagittal arm (6.9 cm). This equation is as follows:

$$\boldsymbol{C_{L5-S1} = 9.81 \times \left\{0.0167(BW)(H)\sin\theta + 0.145(L)(HB) + 0.8\left(\frac{BW}{2} + L\right) + 23\right\}} \quad \text{Eq.2}$$

C_{L5-S1} is the estimated compressive force in N, BW denoted body weight in kg, H represents body height in cm, HB is anterior hand distance from L5-S1 in cm, L equals hand load in kg, and θ indicates the trunk sagittal flexion angle from the vertical axis in degree.

Simple Polynomial Equation

This equation (Mcgill et al. *[22]*) takes the form of a third-order polynomial that estimates the compression force at L4-L5 level as a function of external movements derived from an EMG model of the trunk. This spine model (based on Mcgill et al.'s study) consists of 90 muscles with a rigid thorax, rigid pelvis, and includes five lumbar vertebrae. Rotational springs that represent moment resistance of lumbar segments in three planes bound these vertebrae together. The Polynomial is obtained from performing a regression analysis on the model's outputs (L4-L5 compression force) measured from several slow dynamic tasks. Muscle forces are estimated in a way that moment equilibrium holds at all lumbar joints. The Polynomial is written as follows:

$$\boldsymbol{C_{L4-L5} = 1067.6 + 1.219F + 0.083F^2 - 0.0001F^3 + 3.229B + 0.119B^2 - 0.0001B^3 + 0.862T + 0.393T^2 - 0.0001T^3} \quad \text{Eq.3}$$

F, B, and T are flexion/extension moment, lateral bending moment, and axial twisting moment, respectively.

Linked-Segment Biomechanical Model (LSBM)

The LSBM tool (Potvin *[23]*) calculates the compression force at the L5-S1 level on a single-level (i.e., L5-S1) two-dimensional model. L5-S1 joint coordinates, subject's weight, and distance and magnitude of hand load are required as the inputs to estimate L5-S1 reaction forces. A single equivalent back muscle with a constant sagittal moment arm (6.0 cm to the joint center) produces the extensor moment. This model is expressed as follows:

$$\boldsymbol{C_{L5-S1} = \frac{M_{L5-S1}}{0.06} + \sin(TA) \times (Wt_{LD} + Wt_{cm})} \quad \text{Eq.4}$$

TA is the trunk angle between the horizontal line and the line connecting L5-S1 and C7-T1 (in degrees). Wt_{LD} is the weight of the load (N), Wt_{cm} is the weight of the upper body set equal to 54% of the whole body weight, and M_{L5-S1} is the moment of external loads about the L5-S1 (Nm).

Results

Considering the in vivo measurements reported by Wilke[6] as the point of reference, *Tables 2 to 5* shows that there is a significant disparity between the results of the seven tools. OpenSim and AnyBody showed a better agreement with in-vivo modeling. AnyBody estimated a greater force at the L5-S1 and L4-L5 compared with Arjamand Equation and 3DSSPP, while OpenSim predicted shear forces unrealistically, shear forces were calculated by AnyBody accorded with in-vivo results. Shear forces predicated by 3DSSPP were almost identical to AnyBody results and differed from OpenSim results.

In Tables 2 to *5*, we juxtaposed our results with the results from Rajaee *et al.* (12*)*. As mentioned before, we employed the ANNs model to predict the body postures, while Rajaee utilized the motion capture method to obtain the body postures. By investigating each tool, it is evident that AnyBody yielded the most accurate results. However, this method was not easy to implement, and in terms of time efficacy, it was not efficient as well. The Arjmand regression models estimated forces with a 13.5% mean error relative to the in-vivo measurements (Table 6*)*.

In comparison to AnyBody, the Arjmand regressions had easy-to-compute formulas. This feature, along with employing ANNs to predict body postures (instead of using motion capture techniques), makes this method feasible for real-time applications at workplaces. It is worth noting that the mean error for shear and compression prediction showed a good accuracy with less than 20% and 10% errors, respectively *(*Table 6*)*. Overall, the results suggested the reliability of our study.

Discussion

None of the models in this study estimated the spine forces higher than 3400N. Hence, according to NIOSH criteria, no activity poses a threat to the safety of the workers. However, in case if asymmetry increases or the weight distances from the body such as task 16, estimated forces approach to 3300N, and by factoring 10% error in calculations, NIOSH criterion classifies these types of activities harmful. Furthermore, Davis and Parnianpour *[24]* also developed a method based on the compressive strength for the L4 vertebral level. Multiple parameters, including age, bone mineral content, line bone mineral density, and bone mineral density, were compared for a group of healthy people (23 men and 21 women), and eventually, compression above 4729N was announced as a high risk. Fracture risk of index can be estimated as the net compressive force of an activity to the ultimate strength based on bone mineral density and geometry of the vertebrae *[24-26]*. Regarding these criteria, still no simulated activity exceeds the 4729N limit. However, as the load is placed further away from the body or as the asymmetry increases, the compression and shear forces increase exponentially and so does the risk of damage to the endplate and intervertebral discs.

Both 3DSSPP and AnyBody estimated approximately equal values for the shear forces, which outlined the importance of measuring and applying accurate body postures during various activities for a better shear calculation. Predicted compressive forces by OpenSim were in higher agreement, compared to the shear forces, with AnyBody and in-vivo results (Wilke et al.*[6]*) as well. The number of muscles modeled in OpenSim and AnyBody was considerably higher than other models, which is a contributing reason to the higher accuracy of these two models. Potvin and Merryweather incorporated a single equivalent back muscle, which led to higher errors in the prediction of forces. By taking a closer look at the results of *Tables 2* to *5*, it is seen that accurate predictions of forces for a variety of activities coupled with its easy-to-use feature makes Arjmand predictive regression model to a preferable choice, among its counterparts such as AnyBody, to predict risk factors associated with workplaces. Furthermore, the outputs from Arjmand models *[19, 20]* are in agreement with in-vivo studies *[6]*. Using The ANNs developed by Gholipour and Arjmand *[14]* in conjunction with the Arjmand regression equation is a simple and time-efficient method to monitor workers remotely and to reduce the risk of performing lifting and reaching tasks in a harmful manner. Our results show that occupational risk factors are deteriorated as an activity is performed in more asymmetric ways, or the hand load is placed at a far distance relative to the body. Furthermore, our results for various tasks are in line with the findings of Rajaee's study *[12]*. The only difference between this study and *[12]* is that we implemented an ANN to calculate body postures trained based on in vivo data.

Limitations

This study was limited to the static activities with and without hand loads, and body postures were only obtained for constant body weight and height; thus, intrasubject variances were not investigated. The ANN was trained to replicate posture of ordinary people, while a daily worker may activate different muscles or adopt other postures to reach and lift weights. Nonetheless, ANN was trained at a moving range other than desired activities, and this might cause an error in outputs, particularly near and out of moving ranges of training data. Another downside of this study was about the limitations of each model, such as the number of included muscles in each model or their feasibility to predict forces at L5-S1 and L4-L5 levels.

Conclusion

In this study, we examined the outputs of 7 biomechanical models using an ANN-based posture prediction tool to compare their accuracy with respect to marker-based models. As seen, AnyBody provided the most accurate results for L5-S1 and L4-L5 forces. This accuracy was attributed mostly to its exact anatomical model of the body. This accuracy, however, came at the cost of higher computational time. On the other hand, the Arjmand regression equations had a gratifying accuracy while requiring less computation. The Arjmand regression, in conjunction with the ANN, is a powerful tool for calculation of the risk factors associated with hazardous workplaces in short times. This method can be incorporated at workplaces as a cautionary tool to help reducing the injuries.

Acknowledgement:

Authors greatly appreciate the contributions of Prof. Navid Arjmand and Dr. Rezazadeh in development of this project.

Conflict of interest:

None

Funding support:

None

Authors' contributions:

All authors made substantial contributions to conception, design, acquisition, analysis and interpretation of data.

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