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Identifying the most important predictors of different muscle groups using electromyography, regression models and Artificial Neural Networks in the flat bench press

Authors' Contribution:
A Study Design
B Data Collection
C Statistical Analysis
D Data Interpretation
E Manuscript Preparation
F Literature Search
G Funds Collection

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abstract

Background: The main objective of this study was to determine the input of different muscle groups during the flat bench press with different external loads and to determine whether regression models or Artificial Neural Networks (ANN) models predict sports results more precisely and indirectly better support and optimize the athletes' selection process in the particular strength exercises.

Material and methods: The activity of four muscles was measured in four tasks: the pectoralis major (PM), the anterior deltoid (AD), the lateral head of triceps brachii (TB), and the latissimus dorsi (LD).

Results: The greatest increase in bioelectrical activity with increased external loads was observed on the LD during the descending phase of movement. Then, on the basis of results of 51 athletes, mathematical models were created and an additional study was conducted with the experimental group in order to verify the previously created models which were based on one group of 15 athletes. The regression models and perceptron networks demonstrated their capacity for making generalization and predicting sports results.

Conclusions: The results of the investigation show that the created neural models (9-4-1 structure) offer much higher quality of prediction than a nonlinear regression model.

Key words: non-linear models, ANN, sports results, flat bench press.

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INTRODUCTION

The flat bench press is one of the most popular strength exercises performed by athletes of different sports disciplines. The outcomes gained by strongmen in this competition essentially depend on the level of motor skills acquired through training, abilities to use them in sports technique action, involvement (understood as emotional attitude) and also, but to a lesser extent, tactics in passing out another trial. A successful bench press lift is performed when the barbell is first lowered to the chest and then moved to a fully extended position again. The bench press consists from two phases: the ascending and descending one. The available data regarding bioelectrical activity of particular muscle groups during bench pressing is incomplete [1, 2].

In order to analyze particular motor activities, precise data related to basic variables are necessary. Most relationships in sports science are, unfortunately, not linear. Each unit change in the X variable will not always bring about the same change in the Y variable [2, 3]. Thus, researchers must apply nonlinear tools to describe such phenomena (i.e., nonlinear regression or neural models). A controversy exists related to which model is more accurate in predicting sports results.

It is hypothesized that the neural network modeling will better identify athletes' potential in the flat bench press, compared to a typical regression model [4–7]. Neural networks can be employed wherever a relationship between explanatory variables (inputs) and explained variables (outputs) exists [8,9]. However, they are especially useful for seeking very complex input-output relationships, which are difficult to capture using statistical methods that are usually applied in such cases (e.g., the analysis of relationships or the separation of taxonomically homogenous groups). Given that the relationships between variables may be either linear or non-linear, recently, Artificial Neural Networks (ANNs) have been used more frequently to identify their actual nature. At present, this tool is frequently used for solving the modeling and prediction issues [5–7, 10–12].

This study has had two phases of investigation. During the first one, the main objective was to determine the input of different muscle groups during the flat bench press with different external loads. The second one was intended to determine whether regression models or ANN models predict sports results more precisely and so better support and optimize the athletes' selection processes. An attempt was made to resolve the question which variables are the most informative and can be qualified as explanatory of the regression and neural models.

MATERIAL AND METHOD

participants

The study group consisted of 66 international level athletes (aged 21 ±2.5 yrs, body mass 78.2 ±7.6 kg; height 179.2 ±9.0 cm; 1-repetition maximum [RM] bench press: 121.2 ±12.4 kg) from the Silesian Macro-Region. The written informed consent form was obtained from all participants. The subjects were free from any known cardiovascular or metabolic diseases as reported in a health questionnaire. They were informed of the aim and experimental risks of the study. This project was approved by the Bioethics Committee for Scientific Research at the Academy of Physical Education in Katowice. The authors declare no conflict of interest.

electromyography

The activity of four muscles was measured in four tasks: the pectoralis major (PM) the anterior deltoid (AD), the lateral head of triceps brachii (TB), and the latissimus dorsi (LD). The EMG signals were measured by a Pocket EMG System (BTS Company, Italy). All active channels were the same, and the measuring range was fitted to the subject (typically ±10mV). The analog signal was converted into a digital one with 16 bit sampling resolution and collected on a measure unit.

EMG exercise protocol

After a general warm-up, each subject performed a specific warm-up that consisted of two sets of the bench press with 6 reps at 60%1RM. The 1RM value was used to determine the intensities of particular bouts that were applied during the testing session. The main session included four sets of one rep of the flat bench press with 70%, 80%, 90%, and 100% of 1RM.

data collection

Multidimensional movement analysis was made with the measuring system Smart-E (BTS, Italy), which consisted of six infrared cameras (120Hz) and a wireless module to measure muscle bioelectric activity (Pocket EMG). For further analysis, separate tension values of the 4 chosen muscles were considered during ascending (A), descending (D) and the whole movement (Sum).

In order to test the hypothesis, multidimensional statistical analyses were applied to measurements taken in the construction group. The values of variables measured by means of robust scales and tests were used in multiple regression models. The research problem was addressed using empirical and predictive investigation, based on the data obtained in the form of a multidimensional vector of variables, including independent X_n variables and one dependent variable Y-result. On the basis of results of 51 athletes, mathematical models were created. Then, an additional study was conducted with the testing group, in order to verify previously created models, which were based on one group of 15 athletes.

Numerous characteristics of the participants were measured as independent variables, such as body build, general and specific physical fitness. The most important variables were marked during the electromyography measurements. Two disposable surface electrodes were placed 2 cm apart over the motor points of the pectoralis major (PM) the anterior deltoid (AD), the lateral head of triceps brachii (TB), and the latissimus dorsi (LD) parallel to the muscle's fiber direction. The dependent variables were the results of the bench press. Measurements identified 32 variables. To determine the optimal set of predictors, the R0 vector was determined for the explanatory variables and the R1 vector for the correlations generated by the R0 vector for variables showing a significant correlation with the explained variable Y – the sports result.

This approach allowed for determining 13 predictors which significantly improved the model’s explained variable Y – the sports results. However, four variables were removed from the model following statistical testing (hypothesis testing, significance testing and statistical verification of structural parameters of regression equation for dependent variable Y – within the meaning of the equation: $\text{sign}(r(x_j, y)) = \text{sign}(a_j)$).

Ultimately, the regression equation was re-estimated with the remaining nine explanatory (statistically significant) variables: VmaxD – *maximal velocity during* *the descending phase (B = 1.3)*, AminA – *minimal acceleration during the ascending phase (Beta = 0.6)*, ZA – *anteroposterior displacement during the ascending phase (Beta = 0.5)*, AmaxA – *maximal acceleration during the ascending phase (Beta = 0.8)*, VminA – *minimal velocity during the descending phase (Beta = 0.3)*, TBD – *Triceps Brachii during the descending phase (Beta = 0.4)*, XA – *lateral displacement during the ascending phase (Beta = 0.4)*, YA – *vertical displacement during the ascending phase (Beta = 0.6)*, TD – *time of the descending phase (Beta = 0.7)*.

modelling procedure

The data of 36 athletes which were entered into the neural net and regression models were obtained from one-year measurements. The data set was subdivided into three series: learning series (24 cases), validation series (6 cases) and test series (6 cases). Then, to enhance the model, 15 new training cases were added and estimated again (33 cases – learning series, 9 cases – validation series and 9 cases – test series).

Predictors were confirmed by regression and neural net models for the testing group, comprising a group of 15 other athletes, of the same age and training experience as the construction group, and whose results were not used to build the models. The results of predictions for this group were verified by comparing the model-generated predictions with the actual results achieved by the same group one year later.

statistical analyses

Means and standard deviations were calculated for all variables. The Kolmogorov–Smirnov test of normality and Levene's test of homogeneity of variance were performed to verify the normality of distribution. The comparison of analyzed values before and after the introduction of the experimental factor was carried out with a two-way repeated measures ANOVA. When significant differences were found, Tukey HSD post-hoc tests were used. The effect size (η^2) of each test was calculated for all analyses and was classified according to Hopkins [14]. Statistical significance was set at $p < 0.05$. The multiple stepwise regression was used to select explanatory variables offering the best prediction of athletes' results in the construction phase. These nine predictor variables were log-transformed and used to form regression models predicting Y (results of the bench press).

More formally, in a nonlinear model, at least one derivative with respect to a parameter should involve that parameter. In this study, the $Y_1(t) = \exp(a_1 t + b_1 t^2)$ nonlinear regression model was used and verified after being transformed to linear models using the transformation $Xn_1(t) = \ln Y_1(t)$. For generalization and prediction of sports results, Multilayer Perceptron (MLP) neural models were used to model the bench press with the following structures: 9-2-1, 9-3-1 and 9-4-1. In the Neural Network Statistica Module (NNSM), 100 epochs is the standard procedure, followed by 30 epochs of optimization [15, 16]. The networks were trained using the Levenberg–Marquardt algorithm. The level of significance for all analyses was set at $p \leq 0.05$.

All statistical analyses in both groups of athletes were carried out on a PC using the statistical package STATISTICA 9.1, STATISTICA Neural Networks Module (Release 9) and Excel 2010 from the Microsoft Office 2010.

RESULTS

A two-way repeated measures ANOVA revealed a statistically significant effect of bioelectrical muscle activity in particular muscle groups, during the ascending phase of the lift under different external loads: anterior deltoid activity (ADA – $F = 5.73$, $\eta^2 = 0.245$, $p = 0.001$), triceps brachii activity (TBA – $F = 34.12$, $\eta^2 = 0.631$, $p = 0.001$), latissimus dorsi activity (LDA – $F = 23.22$, $\eta^2 = 0.611$, $p = 0.001$).

The pectoralis major activity (PMA) showed no significant differences in muscle tension in relation to the lifted load (Fig. 1). A verification of data (Levene's test) indicated the greatest increase in bioelectrical activity with increased external loads in the latissimus dorsi during the descending phase of movement ($\eta^2 = 0.618$, $p = 0.011$).

Next, the correlation matrix was made for verification. Results showed no correlation between PMA and the results of bench pressing ($r = 0.01$). Furthermore, very high value of correlation between Y-results of bench pressing and variables: ADA ($r = 0.29$), TBA ($r = 0.56$), LDA ($r = 0.50$) was shown.

The regression model for the bench press results had the following form:

$$\mathbf{Y(SportsResult)=281.8-209.4*VmaxD+780.5AminA+0.3*ZA-25.2*AmaxA-267.2*VminA-112.7*TBD-1.4*XA+0.2*YA-32.3*TD}$$

Using the same variables the perceptron models (multilayer perceptron – MLP) were constructed with the following structures: 9-2-1, 9-3-1 and 9-3-2-1. For networks 9-2-1 and 9-3-1 values of S. D. the ratio for validation series might not be satisfactory. Finally, the use of architecture 9-3-2-1 brought a breakthrough. In the group of 36 athletes, the quality measures for this network were 0.228 for the training subset, 0.284 for the validation subset and 0.278 for the test subset. The results pointed to a good fit between the model and the training data. However, with 15 new training cases added to the model and following model re-estimation, the results improved. The network quality measure for the training subset demonstrated an even better fit between the network and the training data. With regard to new 9-3-2-1 networks, the NRMSE for the learning series was 0.114, and for the validation and test series 0.133 and 0.118, respectively. Thus, the practical usefulness of this model was supported by a large magnitude of correlation coefficients between independent and dependent variables in each group.

Table 1 includes the results of the verification procedure by which the prediction values generated by the nonlinear neural networks and nonlinear regression models for athletes in the bench press ($n = 15$, the new one of the same age and training experience as the construction group, and whose results were not used to build the models), were compared with the actual results for the tested athletes.

Table 1. Predictions for Y- bench press results

N	True Values [kg]	MLP 9-3-2-1			Regression model		
		Calculated Value of Network [kg]	Network Error [kg]	Absolute Network Error [kg]	Calculated Value of Regression [kg]	Regression Error [kg]	Absolute Regression Error [kg]
1	105	105.5	0.5	0.5	106.5	1.5	1.5
2	107.5	108.4	0.9	0.9	108.9	1.4	1.4
3	95	98	3	3	99	4	4
4	120	119	-1	1	117	-3	3
5	115	116.5	1.5	1.5	118	3	3
6	130	129.5	-0.5	0.5	133	3	3
7	125	123.5	-1.5	1.5	126	1	1
8	105	104.5	-0.5	0.5	108	3	3
9	115	115	0	0	115.5	0.5	0.5
10	122.5	121.2	-1.3	1.3	124.8	2.3	2.3
11	117.5	114.7	-2.8	2.8	116.3	-1.2	1.2
12	90	90.5	0.5	0.5	92.4	2.4	2.4
13	122.5	121.5	-1	1	124.7	2.2	2.2
14	140	141.2	1.2	1.2	145.3	5.3	5.3
15	132.5	131.4	-1.1	1.1	133.5	1	1
16	117.5	116.4	-1.1	1.1	119.4	1.9	1.9
17	110	109.5	-0.5	0.5	112	2	2
18	105	104	-1	1	108	3	3
19	115	115.4	0.4	0.4	116.4	1.4	1.4
20	107.5	107	-0.5	0.5	108	0.5	0.5
	Sum:		**-4.8**	**20.8***	Sum:	**35.2**	**43.6***

DISCUSSION

The main objective of the research was to identify the efficiency and predictive usefulness of artificial neural networks treated as an athlete recruitment tool in contrast to the widely used regression models. In order to accomplish the intended goals, an attempt was made to define which variables were the most informative and qualified best to play the role of the models' explanatory variables.

The regression model identified the following predictors as the most important: maximal velocity of the bar during the descending phase, maximal acceleration of the bar during the ascending phase, time of the descending phase and vertical displacement during the ascending phase. The results of the analysis are in accordance with the conclusions of Reynolds et al. [17] and Requena et al [18]. Unfortunately, there is little data about the application of regression and discrimination models in powerlifting. Thus, it is difficult to compare our results to others. Therefore, these variables significantly influenced sports results in the analyzed group of the athletes.

The same variables that were found to be most informative and qualified for the role of explanatory variables in the regression models were used to build the neural models. For the network with a structure 9-2-1, Normalized Root Mean Squared Error (NRMSE) was too high and unsatisfactory to claim that this model adjusted well to learning data (0.478), 0.488 (testing data) and 0.476 (validation data). The network 9-3-1 reached better results than 9-2-1. Results for networks 9-2-1 and 9-3-1 showed problems of decreased ability for generalization [19]. However, the value in validation and test series and the correlation coefficient in those groups (0.96) implicated a necessity to build more models with a larger number of neurons in a hidden layer, which could approximately fit better into the network and learning data in the first set [19]. The quality measures for the network structured as 4-3-2-1 built for the first 40 cases pointed to a good fit between the model and the training data. However, with 20 new training cases added to the model and following model re-estimation, the results improved. Moreover, the quality measures for all the subsets provided strong arguments in favor of the network's high ability to generalize and predict results, and this finding was the main reason for which the investigation was initiated. The practical value of the created model was confirmed by the already mentioned high correlation coefficients: 0.957, 0.961, and 0.979.

In order to test the comparisons of the results that were used to build the regression models and the neural networks, 20 athletes whose results were not built into the models were tested. Their bench pressing results were measured and the quality of the predictions was verified after training. The analysis of the results presented in Table 1 (absolute error modules) shows that the neural models' algorithms are superior to the regression models as far as prediction is concerned. The absolute values of the models' error were different by 22.80 kg favoring the neural model. Additionally, the neural model was of greater accuracy in the case of athletes achieving medium or poor results. The negative total error of the network indicates that the model makes larger errors in athletes with better results in the bench press. The above data on a group of 20-year-old athletes clearly show that the neural model better predicts sports results than the regression model, confirming also findings of Bartlett et al. [20] and Whisenant et al. [21], whose non-linear neural models provided predictions of better quality than the multiple regression models. Murakami et al. [21] indirectly proved that neural models are capable of better predictions than nonlinear or linear regression models. The opinion that networks with a small number of hidden layers (i.e. structure 9-3-2-1 or 9-3-1) should be preferred in constructing neural models for predicting relationships in the field of sport corresponds to the opinion of Shojaie and Michailidis [23] expressed in their study that the networks with one or two hidden layers had the greatest capacity for generalization.

CONCLUSIONS

The results of the investigation show that the created neural models offer much higher quality of prediction than a nonlinear regression model. The former generates smaller prediction errors which directly follow from the absolute error. The optimal set of variables that are the most informative and usable as the explanatory variables of the nonlinear regression models and neural models in the tested group of 20-year-old athletes for Y (results of bench pressing) consists of: *maximal velocity during the descending phase, minimal acceleration during the ascending phase, anteroposterior displacement during the ascending phase, maximal acceleration during the ascending phase, minimal velocity during the descending phase, triceps brachii during the descending phase , lateral displacement during the ascending phase, vertical displacement during the ascending phase, time of the descending phase*.

The study results explicitly demonstrate that the neural models are a tool which is far superior and offers better optimization possibilities in predicting sports results, athletes' recruitment and selection processes, than the widely applied regression models.

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