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EMG ANALYSIS AND MODELLING OF FLAT BENCH PRESS USING ARTIFICIAL NEURAL NETWORKS

Adam MASZCZYK[1], Artur GOŁAŚ[1], Miłosz CZUBA[1], Henryk KRÓL[2], Michał WILK[1], Petr ŠŤASTNÝ[3], Jon GOODWIN[4], Maciej KOSTRZEWA[1] & Adam ZAJĄC[1]

[1] *Department of Sports Theory, Jerzy Kukuczka Academy of Physical Education, Katowice, Poland*
[2] *Department of Biomechanics, Jerzy Kukuczka Academy of Physical Education, Katowice, Poland*
[3] *Faculty of Physical Education and Sport, Charles University in Prague, Czech Republic*
[4] *School of Sport, Health and Applied Science; St. Mary's University, Twickenham, London, England*

ABSTRACT

The objective of this study was to evaluate the contribution of particular muscle groups during the Flat Bench Press (FBP) with different external loads. Additionally, the authors attempted to determine whether regression models or Artificial Neural Networks (ANNs) can predict FBP results more precisely and whether they can optimise the training process. A total of 61 strength-trained athletes performed four single repetitions with 70, 80, 90 and 100% of one repetition maximum (1RM). Based on both kinematic and electromyography results, a regression model and ANNs for predicting the FBP performance was created. In an additional study, 15 athletes performed the training session in order to verify the created model. The results of the investigation show that the created neural models 9-4-1 structure (NRMSE [Normalised Root Mean Squared Error], for the learning series was 0.114, and for the validation and test series 0.133 and 0.118, respectively), offer a much higher quality of prediction than a non-linear regression model (Absolute regression error – Absolute network error =47kg–17kg=30kg).

Key words: Non-linear models; Artificial neural networks; Bench press performance; Electromyography.

INTRODUCTION

The Flat Bench Press (FBP) is one of the most popular strength exercises performed by athletes of different sport disciplines (Van den Tillaar & Ettema, 2009). FBP performance is significantly influenced by the strength and power of several muscle groups and by proper technical execution of the movement (Lehman, 2006). A successful bench press lift is performed when the barbell is first lowered (descending phase) to the chest and then moved to a fully extended position (ascending phase). The recognised primal movers for FBP include the *Pectoralis major* (PM), *Triceps brachii* (TB) and *Anterior Deltoid* (AD), but the performance itself is strongly influence by their antagonists and synergists, such as the *Pectoralis minor*, shoulder external rotators or *Latissimus dorsi* (LD). Understanding the relative contributions of different muscles and the kinematic changes across movement phases with increasing load can help to characterise the benefits and risks of the exercise, and can also improve training effectiveness.

Prediction of one repetition maximum (1RM) by 10RM itself has been studied for the purpose of setting accurate training intensity in the early stage of a training session (Brzycki, 1993; LeSuer *et al*., 1997; Reynolds *et al*., 2006). Many prediction equations take into consideration only the sport results, so in effect the conclusions are in high inaccuracy regarding to different motor tasks (Hoeger *et al*., 1987; LeSuer *et al*., 1997). Current development of technology enables researchers to measure 3D kinematics and muscle activity along with different exercise intensities. By the recognition of Hills curve, there are three parameters, which influence muscle strength production: length of muscle, muscle excitation and speed of contraction (Siff, 2003). The kinematics variables are described by movement acceleration, while the bioelectrical activity can describe the level of muscle excitation. The FBP during 1RM is recognised in importance of electromyography (EMG) mean amplitude for PM, AD and LD (Santana *et al*., 2007), but their study did not refer to the activity of the TB. In the study of Van Den Tillaar and Ettema (2009), FBP showed the same pattern of muscle activity, yet there were differences in kinematics. Thus, the 1RM flat bench press performance model should be described in a more complex form and by innovative methods.

The prediction of exercise performance is complex and dependent on the modelling of frequently non-linear interactions (Zehr, 2005; Van Den Tillaar & Ettema, 2009). Non-linear tools (non-linear regression and neural models), are available to describe such phenomena. However, there is no agreement over the relative accuracy of such methods in predicting results (Maier *et al*., 2000; Zehr, 2005; Maszczyk *et al*., 2012). It is hypothesised that neural network modelling will better identify the potential of athletes in the FBP, compared to a typical regression model (Jolivet *et al*., 2008; Rahmani *et al*., 2009; Trebs *et al*., 2010; Maszczyk *et al*., 2011).

Neural networks can be employed wherever a relationship between explanatory variables (inputs) and explained variables (outputs) exists (Gregor & Pink, 1985; Haykin, 1994). 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 (for example, the analysis of relationships or the separation of taxonomically homogenous groups). Considering 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 (Lees, 2002; Bartlett, 2006; Maszczyk *et al*., 2011). At present, this tool is used frequently for solving modelling and prediction issues (Maier *et al*., 2000; Lees, 2002; Zadeh, 2002; Bartlett, 2006; Maszczyk *et al*., 2012).

PURPOSE OF STUDY

There were two objectives of this study: to determine the differences in EMG amplitude due to increased exercise intensity (70, 80, 90 and 100% of 1RM); and to create an ANNs prediction model for 1RM FBP performance and to determine the accuracy between ANNs prediction and typical regression prediction. Therefore, this study had two distinct phases of investigation. During the first one, the main objective was to determine the EMG activity of particular muscle groups during the FBP with different external loads. The second was intended to determine whether regression models or ANNs predict sport results more precisely and was the primary goal of this investigation.

METHODOLOGY

Participants

The study group consisted of 61 strength trained sportsmen (aged 23±2yrs, body mass 79.2±3.6kg; body height 180.2±4.0cm; 1RM bench press: 90±12.4kg), from the MAX FIT CLUB POLAND. The participants (N=36) were selected randomly (from 75 sportsmen) for the construction group (CG) for the construction of the first model and 15 subjects were chosen for the new training cases group (NTC), in order to construct the model. Then, 10 participants were selected (whose results were not built into the models), to be included as a test group (TG) for the second session (verification of models prediction).

The core investigation was preceded by 3 months of general and specific physical fitness training in own clubs and in the Academy of Physical Education in Katowice (APEK) facilities. Each sportsman participated in 3 training sessions per week in his own sport club and 3 additional training sessions per week in the APEK facilities, for the purpose of this research. Written informed consent was obtained from all participants. The subjects were free from any upper limb injury, and had no cardiovascular or metabolic diseases as reported in a health questionnaire. Subjects with upper limb injury or previous surgery were excluded from the research group. The Bio-ethics Committee for Scientific Research at the Academy of Physical Education in Katowice approved the project.

Test protocol

After a general warm-up performed with recommendations of the American Society of Exercise Physiology (Brown & Weir, 2003), each subject performed a specific warm-up that consisted of 2 sets of 6 repetitions of the FBP with a load of 60% 1RM. The test protocol included 4 sets of 1 repetition of the FBP with 70, 80, 90 and 100% of 1RM. The participants performed a traditional bench press (descending and ascending the barbell). No marked pause between descending and ascending the barbell was necessary. However, the participants were not permitted to 'bounce' the barbell off the chest and were not allowed to raise the lower back from the bench.

3D Kinematics and electromyography

Multidimensional movement analysis was made with the Smart-E measuring system (BTS, Italy), which consisted of 6 infrared cameras (120Hz) and a wireless module to measure muscle bioelectric activity (Pocket EMG 1kHz, pass band 10-500Hz, 16 channels). Modelling in 3D space, as well as calculations of parameters was performed with the help of Smart software (Smart Capture, Smart Tracker and Smart Analyser, BTS, Italy). The set of passive markers permissive on delimitation of chosen parameters of the barbell and the participant was applied. Technical accuracy of the system after the calibration process equalled 0.4mm (the distance between 2 markers in 3D). The motion of the bar in every repetition was divided into 2 phases: descent ($_D$) and ascent ($_A$) ones.

TABLE 1. **STANDARDISED VARIABLES USED TO CONSTRUCT MODELS**

Variables	**Mean**	**SD**	**CV**
Y1(FBP)	0.708	0.851	-0.755
PMD	-0.358	-0.432	-0.381
PMA	-0.357	-0.432	-0.515
PMsum	-0.352	-0.422	-0.540
ADD	-0.359	-0.431	-0.195
ADA	-0.357	-0.428	-0.301
ADsum	-0.352	-0.418	-0.354
TBD	-0.362	-0.438	-0.023
TBA	-0.360	-0.433	-0.306
TBsum	-0.357	-0.429	-0.339
LDD	-0.364	-0.442	-0.027
LDA	-0.363	-0.441	-0.184
LDsum	-0.363	-0.440	-0.208
XD	-0.174	0.138	0.079
XA	-0.168	0.285	0.375
YD	3.556	3.373	-0.860
YA	3.773	2.950	-0.929
ZD	0.817	1.507	-0.554
ZA	0.760	2.015	-0.312
VmeanD	-0.361	-0.439	-0.509
VmaxD	-0.359	-0.435	-0.515
VminD	-0.364	-0.442	1.433
VmeanA	-0.361	-0.438	-0.414
VmaxA	-0.359	-0.435	-0.479
VminA	-0.364	-0.441	3.509
AmeanD	-0.357	-0.424	-0.080
AmaxD	-0.335	-0.383	-0.359
AminD	-0.364	-0.440	2.490
AmeanA	-0.355	-0.419	-0.006
AmaxA	-0.330	-0.385	-0.520
AminA	-0.364	-0.441	2.421
TD	-0.347	-0.414	-0.512
TA	-0.347	-0.399	-0.128

SD= Standard Deviation CV= Coefficient of Variances

Considering the data describing the kinematics of the bar, the following variables were calculated to define a quantitative motion of the bar. Before the 1-RM experimental test, the skin was prepared (shaved, washed with alcohol, abraded), for the placement of gel coated surface EMG electrodes. Electrodes (11mm contact diameter) were placed on the dominant side of the body on the belly of the muscle in the presumed direction of the underlying muscle fibres with a centre-to-centre distance of 2.0cm according to the recommendations by SENIAM (Hermens *et al*., 2000).

PM electrodes were positioned halfway between the sternal notch and anterior auxiliary line. AD electrodes were placed 2 finger-breadths below the acromio-clavicular joint and angled towards the deltoid tuberosity. The electrodes for the TB were positioned mid-way between the acromion and olecranon processes on the posterior portion of the upper arm on the long head of the triceps. LD electrodes were placed in the middle part of the muscle, at the height of spinous process of the first lumbar vertebra. A ground electrode was placed directly over the right anterior-superior iliac spine. This method of electrode placement was similar to that of Cram and Kasman (1998). The normalisation procedure (MVIC) was carried out in accordance with the recommendations by SENIAM (Hermens *et al*., 2000; Konrad, 2005).

In order to test the hypothesis, multidimensional statistical analyses were applied to measurements taken in the construction group (CG). The research problem was addressed by using an empirical and predictive investigation, based on the data obtained in the form of a multidimensional vector of variables, including independent X_n variables and 1 dependent variable Y-bench press results (1RM). Based on the results of the 51 participants, mathematical models were created. Then, an additional study was conducted on a group of 15 participants, in order to verify previously created models.

Numerous characteristics of the participants were measured and served as the independent variables, and included specific variables of the bench press (Table 1). The dependent variables included the results of the bench press. During the measurements, 32 variables were identified. 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 Y1 – FBP result.

This approach allowed determining 13 predictors, which significantly improved the models explained by variable Y1 (the result of the FBP). The mean values of this variable were used in the multiple regression models. However, 4 variables were removed from the model following statistical testing (testing the significance of the hypothesis and statistical verification of structural parameters of regression equation for dependent variable Y1- 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 9 explanatory (statistically significant) variables:

$Vmax_D$= Maximal velocity during the descending phase (B=1.3)
$Amin_A$ = Minimal acceleration during the ascending phase (Beta=0.6)
Z_A = Anterior-posterior displacement during the ascending phase (Beta=0.5)
$Amax_A$ = Maximal acceleration during the ascending phase (Beta=0.8)

$Vmin_A$ = Minimal velocity during the descending phase (Beta=0.3)
TB_A = *Triceps brachii* during the ascending phase (Beta=0.4)
X_A = Lateral displacement during the ascending phase (Beta=0.4)
Y_A = Vertical displacement during the ascending phase (Beta=0.6)
T_D = Time of the descending phase (Beta=0.7)

Modelling procedure

The data of the CG were entered into the neural net and regression models were obtained from the measurements using the Smart-E system (BTS), which identified 32 independent variables. The data set was subdivided into 3 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; 9 cases: test series). Regression and the neural net models confirmed the predictors for the TG, who was of the same age and had the same training experience as the CG, and whose results were not used to construct the models. So, the results of the predictions for the TG were verified by comparing the model-generated predictions with the actual results achieved by the same group 3 months later.

Statistical analysis

The EMG and kinematic parameter results of the first session were expressed as group means and standard deviations were calculated for all the variables. The Kolmogorov-Smirnov test of normality and Levene's test of homogeneity of variance were performed to verify the normality of the distribution. The 1-way ANOVA was applied to determine the statistical differences in EMG amplitude due to increased exercise intensity (70, 80, 90 and 100% of 1RM).

Regression and neural network models

Multiple stepwise regressions were used to select the explanatory variables offering the best prediction of results in the CG. These 9 predictor variables were log-transformed and used to form regression models predicting Y (results of the FBP).

More formally, in a non-linear model, at least 1 derivative with respect to a parameter should involve that parameter. In this study, the $Y_1(t)=\exp(a_1t + b_1t^2)$ non-linear regression model was used and verified after being transformed to linear models using the transformation $X_{n1}(t)=\ln Y_1(t)$. For generalisation and prediction of sport results, Multilayer Perceptron (MLP) neural models were used to describe 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 optimisation (Szaleniec *et al.*, 2006, 2008). The networks were trained using the Levenberg-Marquardt algorithm. The level of significance for all analyses was set at $p \leq 0.05$.

Testing data verifying model-generated predictions

The primary goal of the investigation was to compare and assess the predictive abilities of the non-linear regression and neural models. This necessitated testing the prediction values against the actual FBP results. After data collection, regression and neural models were built and a second phase of research was conducted. One month after the beginning of the investigation, 15 participants performed the same training protocol as the first sample, and once again, independent variables were measured. FBP results were predicted using the above regression and neural models for the TG (n=10). Three months after the prediction of the bench press using these models, their results were recorded (true values). Model-generated predictions were compared to actual results (kg), and absolute errors were calculated. The calculation of absolute errors was dictated by the specificity of the regression models.

The regression function is built upon the method of least squares in which the sum of the squares in the numerator of the function must approximate as closely as possible that of the denominator. This creates a situation in which the model predicts results with great deviation, yet after adding up the deviations, the error will be close to zero. Thus, the model does not possess highly specific predictive possibilities. Only after adding up the values of absolute deviations in the neural and regression models can the superiority of non-linear neural models be detected, in which the absolute error is much smaller than in the regression models (Table 1). All statistical analyses in both groups of sportsmen were carried out on a PC using the statistical package *STATISTICA 9.1*, *STATISTICA* Neural Networks Module (Release 9) and *Excel 2010* from Microsoft Office 2010.

RESULTS

Numerous characteristics of the participants were measured, which served as independent variables and included specific variables of bench press (Table 1). All variables were normally distributed as suggested by the Kolmogorov-Smirnov test results. One-way ANOVA revealed statistically significant differences in EMG amplitude for the variables due to increased exercise intensity between 70 and 100% only:

Pectoralis major EMG amplitude (MVIC) during descending phase (PM_D);
Anterior deltoid EMG amplitude (MVIC) during descending phase (AD_D);
Anterior deltoid EMG amplitude (MVIC) during ascending phase (AD_A);
Triceps brachii EMG amplitude (MVIC) during descending phase (TB_D);
Triceps brachii EMG amplitude (MVIC) during ascending phase (TB_A);
Latissimus dorsi EMG amplitude (MVIC) during descending phase (LD_D); and
Latissimus dorsi EMG amplitude (MVIC) during ascending phase (LD_A).

TABLE 2. **ONE-WAY ANOVA IN EMG ACTIVITY OF MUSCLES AMPLITUDE BETWEEN 70% AND 100% 1-RM**

Variables	F	p
PM_D	6.588	0.014
AD_D	4.501	0.040
AD_A	5.737	0.021
TB_D	23.114	0.001
TB_A	34.117	0.001
LD_D	14.382	0.005
LD_P	23.216	0.001

The results of 1-way ANOVA suggested that if 1 or more muscles will be determined by a matrix for models, one could optimise their function for the best sport results (Y1-FBP). Table 2 shows the results of the 1-way ANOVA, which revealed a statistically significant difference in EMG amplitude due to increased exercise intensity between 70 and 100% only.

The regression model for the FBP results had the following form:

$$Y1(FBP) = 281.8 – 209.4*Vmax_D + 780.5\ Amin_A + 0.3*Z_A – 25.2*Amax_A – 267.2*Vmin_A – 112.7*TB_A – 1.4*X_A + 0.2*Y_A – 32.3*T_D$$

where:

$Y1$ =	1RM FBP result (kg)
$Vmax_D$ =	Maximum velocity during descending phase (m/s)
$Amin_A$ =	Minimal acceleration during ascending phase (m/s^2)
Z_A =	Anterior-posterior displacement during the ascending phase
$Amax_A$ =	Maximal acceleration during ascending phase (m/s^2)
$Vmin_A$ =	Minimal velocity during ascending phase (m/s)
TB_A =	*Triceps brachii* EMG amplitude (MVIC) during ascending phase
X_A =	Lateral displacement during the ascending phase (mm)
Y_A =	Vertical displacement during the ascending phase (mm)
T_D =	Total time of the descending phase (%)

Using the same variables of the perceptron models (Multilayer Perceptron: MLP) were constructed with the following structures: 9-2-1 (Normalised Root Mean Squared Error/NRMSE: learning data=0.478; testing data=0.488; validation data=0.476) and 9-3-1 (NRMSE: learning data=0.363; testing data=0.321; validation data=0.355). For networks 9-2-1 and 9-3-1, values of NRMSE for validation series were not satisfactory. Finally, the use of architecture 9-4-1 brought a breakthrough. For the group of 36 sportsmen, 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.

However, with the 15 new training cases added to the model and following model re-estimation, the results improved. With regard to the new 9-4-1 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 correlation coefficients of a large magnitude between independent and dependent variables in each group.

Table 3 includes the results of the verification procedure by which the prediction values generated by the non-linear neural networks and non-linear regression models for the sportsmen (n=10, the new group of the same age and the same training experience as the CG, and whose results were not used to build the models), in the FBP were compared with the actual results for the tested sportsmen.

TABLE 3. **TRUE AND CALCULATED VALUES FOR Y1 VARIABLE OF FBP 1RM**

		MLP 9-4-1			**Regression model**		
Athlete	True values [kg]	Calculated network value [kg]	Network error [kg]	Absolute network error [kg]	Calculated regression value [kg]	Regression error [kg]	Absolute regression error [kg]
1	85.00	90.00	-5.0	5.0	100.50	-10.5	10.5
2	90.00	90.50	0.5	0.5	87.50	5.0	5.0
3	92.50	92.00	1.0	1.0	97.00	5.5	5.5
4	102.50	101.50	-2.5	2.5	91.00	-3.5	3.5
5	87.50	90.00	-0.5	0.5	97.00	-2.0	2.0
6	95.00	95.50	-2.5	2.5	103.50	-3.5	3.5
7	100.00	102.50	-2.0	2.0	88.50	-3.5	3.5
8	85.00	87.00	-1.0	1.0	108.50	-3.5	3.5
9	105.00	106.00	-1.5	1.5	95.00	-5.0	5.0
10	90.00	91.50	-0.5	0.5	85.00	5.0	5.0
		Sum:	**-14.0**	**17***	**Sum:**	**-16.0**	**47***

DISCUSSION AND CONCLUSIONS

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

The regression model identified the following predictors of sport results (Y1-FBP) 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 Requena *et al*. (2005) and Reynolds *et al*. (2006). Moreover, Van den Tillaar and Ettema (2009) also confirm that the maximum velocity during the descending phase (V_{maxD}), and lateral displacement during the ascending phase (X_a), is one of the most important parameters determining sport results - Y1-FBP. Unfortunately, there is little data about the application of regression and discrimination models in power lifting thus; it is difficult to compare the results of the current study to that of other studies. Therefore, these variables significantly influenced the sport results in the considered group of sportsmen.

The same variables that were found to be most informative and qualified for the role of the explanatory variables in the regression models were used to build the neural models. For the network with a structure 9-2-1, NRMSE was too high and not satisfactory to claim that this model adjusted well. The network 9-3-1 reached better results than 9-2-1, yet networks 9-2-1 and 9-3-1 showed problems of decreased ability for generalisation (Kurz & Stergiou, 2005). However, the value in validation and test series and the correlation coefficient in those groups (0.96), indicated a necessity of building 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 (Kurz & Stergiou, 2005). The quality measures for the network structured as 9-4-1 built for the first 36 cases 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. Additionally, the quality measures for all subsets provided strong arguments in favour of the network's high ability to generalise and predict results and this finding was the main reason for why 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, 10 sportsmen whose results were not built into the models were tested. Their FBP 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 were superior to the regression models, as far as the prediction was concerned. The absolute values of the models' error differed by 30kg in favour of the neural model. Additionally, the neural model was of greater accuracy in cases of sportsmen achieving average or poor results. The negative total error of the network indicates that the model makes larger errors in sportsmen with better results in the FBP.

The data collected on a group of 23-year-old sportspersons clearly showed that the neural model predicted sport results better than the regression model, confirming the findings of Bartlett *et al*. (1996), whose non-linear neural models provided predictions of better quality than the multiple regression models. Murakami *et al*. (2005) indirectly proved that neural models are capable of better predictions than non-linear or linear regression models. The opinion that networks with a small number of hidden layers (structure 9-4-1 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 (2010), expressed in their study, that the networks with one or two hidden layers had the greatest capacity for generalisation.

This study is limited by the number of measured muscle groups, which can be attributed to the shortcomings of the measuring instrument. Another limitation of the study includes the choice of variables evaluated. Only kinematic variables were considered, while individual genetic profiles were not, yet they can significantly influence power (acceleration) and the result of the FBP (Petr *et al*., 2014). The small number of cases can also be considered a limitation of the study, especially when testing the regression model (Maszczyk *et al*., 2012).

The results of the investigation show that the created neural model (9-4-1), offers much higher quality of prediction than created earlier with the regression model for Y1 (FBP). The former generates smaller prediction errors, which directly follow from the absolute error. The optimal set of variables that are most informative and usable as explanatory variables of the non-linear regression models and neural models, for the tested group of the 23-year-old sportsmen for Y1 (FBP results) consists of: maximal velocity during the descending phase; minimal acceleration during the ascending phase; anterior-posterior displacement during the ascending phase; maximal acceleration during the ascending phase; minimal velocity during the descending phase; *Triceps brachii* activity during the ascending phase; lateral displacement during the ascending phase; vertical displacement during the ascending phase; and the time of the descending phase.

The results explicitly demonstrate that neural models are a tool, which is useful in predicting FBP performance, classifying sportspersons and in optimising the training process.

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Dr Artur GOŁAŚ: Department of Sports Theory, The Jerzy Kukuczka Academy of Physical Education, 40-065 Katowice, Mikolowska 72a Str., Poland. Tel.: +48 668 130 099, E-mail: a.golas@awf.katowice.pl

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