2020

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International Journal of Sports Physiology and Performance, 2020, 15, 285-287
https://doi.org/10.1123/ijspp.2019-0009

Human Kinetics
BRIEF REPORT

Use of Machine Learning to Model Volume Load Effects on Changes in Jump Performance

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Purpose: To use an artificial neural network (ANN) to model the effect of 15 weeks of resistance training on changes in countermovement jump (CMJ) performance in male track-and-field athletes. ***Methods:*** Resistance training volume load (VL) of 21 male division I track-and-field athletes was monitored over the course of 15 weeks, which covered their indoor and outdoor competitive season. Weekly CMJ height was also measured and used to calculate the overall 15-week change in CMJ performance. A feed-forward ANN with 5 hidden layers was used to model how the VL from each of the 15 weeks was associated with the overall change in CMJ height. ***Results:*** Testing the performance of the developed ANN on 4 separate athletes showed that 15 weeks of VL data could predict individual changes in CMJ height with an average error between 0.21 and 1.47 cm, which suggested that the ANN adequately modeled the relationship between weekly VL and its effects on CMJ performance. In addition, analysis of the relative importance of each week in predicting changes in CMJ height indicated that the VLs during deload or taper weeks were the best predictors (10%–17%) of changes in CMJ performance. ***Conclusions:*** ANN can be used to effectively model the effects of weekly VL on changes in CMJ performance. In addition, ANN can be used to assess the relative importance of each week in predicting changes in CMJ height.

Keywords: artificial neural network, countermovement jump, sports, periodization, track and field

For sports where performance depends on the ability to generate high mechanical impulse, such as the sprints or throws in track and field, resistance training generally constitutes a large portion of the training process.[1] Optimal physiological adaptations to resistance training programs depend, in large part, on adequate prescription and progression of training loads.[1–3] For strength and power training, training loads are most commonly quantified by the volume load (VL) of a given workout, whereas the physiological adaptations are commonly assessed with jumping exercises, such as the squat (SJ) or countermovement jumps (CMJ).[3–5] Importantly, changes in SJ and CMJ performance appear to be correlated with training loads.[4,5] For example, reductions in training load during a taper occur concurrently with increases in CMJ performance of track-and-field throwers.[4] In addition, changes in SJ performance correlate with changes in training loads over the course of a competitive season in men's college soccer players.[5] Although these studies provide evidence that training loads affect neuromuscular performance, they do not afford detailed insights into how to optimize physiological adaptations based on the relationship between training loads and performance outcomes.

As optimizing neuromuscular adaptations depends on appropriate prescription and progression of training loads, several models have been used to probe and elucidate the association between training loads and performance outcomes.[6,7] Traditionally, work in the field of load monitoring has used a systems-model approach, which aims to facilitate our understanding of how information about the training process can be used to predict an athlete's readiness and potential for performance.[6,7] More recently, researchers have used artificial neural networks (ANNs) for the same purposes.[8–10] For example, ANNs were used to successfully predict swimming performance from 4 weeks of training load data, which included weekly training volume for swim-related activities, resistance exercise, and dryland training.[8]

Artificial neural networks also effectively model complex, nonlinear relationships better than other techniques (eg, regression) and do not rely on deterministic or reductionistic principles.[9,10] However, while ANNs provide effective models for sports science problems, they are often criticized as "black boxes" that do not provide mechanistic insight into the relationships between training loads and performance outcomes, and thus exhibit only limited usefulness for helping coaches understand these relationships.[3] This criticism, however, may be overcome through analysis of the connection weights between ANN layers.[11] The connection weights algorithm acts as a variable selection method that can help identify which input variables contribute to a network's capacity to predict the respective output variables.[11]

The purpose of this study was to use an ANN to model the effect of 15 weeks of resistance training on changes in CMJ performance in male track-and-field athletes. It was hypothesized that the ANN would be able to effectively model the association between training load and changes in CMJ height and be able to identify the relative importance of specific training weeks on the CMJ changes.

Methods

Subjects

Twenty-one male division I track-and-field athletes (mean [SD]: age: 20.7 [0.9] y, body height: 1.79 [0.05] m, body mass: 77.0 [4.2] kg, maximum CMJ height: 86.7.2 [8.8] cm) participated in this study. Each athlete provided written informed consent. The study was approved by Marquette University's Institutional Review Board for human subjects testing.

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Design

Athletes participated in CMJ test sessions at the beginning and end of a periodized resistance training program, which covered the competitive collegiate indoor (January to March) and outdoor (March to May) season, and lasted for 15 weeks (Table 1). All athletes had completed a 15-week off-season resistance training program the previous fall (August to December) and were well familiar with the CMJ testing procedures. Prior to the CMJ test sessions, athletes performed a brief warm-up that included calisthenic and body-weight exercises (eg, squats and lunges). All CMJ test sessions occurred immediately before the daily resistance training sessions. While not all athletes completed these sessions at the same time of day, the time of pretesting and posttesting remained consistent for individual athletes.

Methodology

A jump mat (Just Jump; Probotics Inc, Huntsville, AL) was used to assess CMJ heights (in centimeter). The jump mat demonstrates acceptable reliability for intrasession (intraclass correlation coefficient: .92, coefficient of variation: 4.2%) and intersession (intraclass correlation coefficient: .84, coefficient of variation: 6.3%) CMJ testing.[12] Two CMJs were performed during each test session, and the best CMJ height was used for analysis. Training load was quantified through VL (in kilogram), which was calculated by multiplying the total reps and weight lifted for each workout and then summed for each week. VL was calculated only for major compound exercises (ie, clean and back squat).

Statistical Analysis

A feed-forward ANN was used to model the association between the VL and changes in CMJ performance (Figure 1). Weekly VLs from the 15 training weeks were used as predictor variables in the input layer. The hidden layer consisted of 5 neurons. The output layer consisted of the pre–post season change in CMJ height. Data from 21 athletes were randomly divided into training (n = 13), validation (n = 4), and testing (n = 4) sets. The training set was used to train the weights and biases of the ANN with Levenberg–Marquardt backpropagation. The validation set was used for "early stopping" of the training process to help prevent overfitting and improve generalizability. The test set was used to determine how the trained ANN would perform when it was presented with completely new (ie, separate) data. For all sets, performance was assessed through the coefficient of determination (r^2), root mean square error (RMSE), and the 95% confidence interval for the RMSE. The relative importance of each input variable was calculated with the connection weights method and expressed as a percentage that shows the relative contribution of each predictor based on its input-hidden layer weights and hidden-output layer weights.[12] The ANN and connection weights algorithm were implemented in MATLAB (The MathWorks, Natick, MA).

Results

The average increase in CMJ height over the 15 training weeks was 4.1 (4.1) cm. The average weekly training VL ranged from 1324 (183) to 3530 (502) kg (Figure 2).

The r^2 for training, validation, and testing were .99, .97, and .89, respectively. The RMSE and 95% confidence interval (lower bound, upper bound) for training, validation, and testing were 0.63 (0.3, 0.96), 0.49 (0.07, 0.91), and 0.84 (0.21, 1.47) cm, respectively. The relative importance of the weekly training volume in predicting CMJ height change ranged from 1% to 17% (Figure 2).

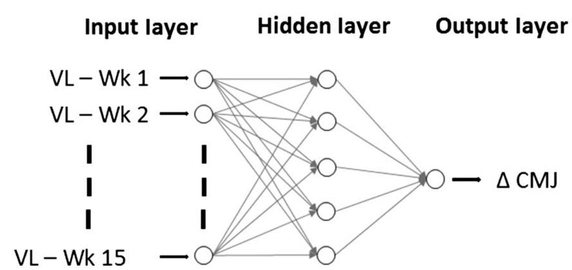

Figure 1 — Architecture of the artificial neural network used to model the relationship between 15 weeks of resistance training volume load (VL [kg]) data and changes in countermovement jump (Δ CMJ [cm]) performance.

Table 1 Weekly Training Volume (Set and Reps) and Intensity (% 1RM) for the Indoor and Outdoor Seasons of the Track-and-Field Athletes in the Current Study

	Week of indoor season							Week of outdoor season							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Clean															
Set 1	1 × 70%	1 × 75%	1 × 75%	1 × 75%	2 × 70%	2 × 75%	2 × 85%	4 × 50%	4 × 50%	4 × 55%	4 × 55%	1 × 70%	1 × 75%	1 × 75%	1 × 75%
Set 2	1 × 75%	1 × 80%	1 × 80%	1 × 80%	2 × 75%	2 × 80%	2 × 90%	4 × 50%	4 × 55%	4 × 55%	4 × 60%	1 × 75%	1 × 80%	1 × 80%	1 × 80%
Set 3	1 × 80%	1 × 80%	1 × 85%	1 × 85%	2 × 80%	2 × 85%		4 × 55%	4 × 55%	4 × 55%		1 × 80%	1 × 80%	1 × 85%	1 × 85%
Set 4	1 × 80%	1 × 85%	1 × 85%		2 × 80%			4 × 60%	4 × 60%	4 × 60%		1 × 80%	1 × 85%	1 × 85%	
Back squat															
Set 1	2 × 70%	2 × 75%	2 × 80%	2 × 80%	1 × 70%	1 × 75%	1 × 85%	4 × 20%	4 × 20%	4 × 20%	4 × 20%	2 × 70%	2 × 75%	2 × 80%	2 × 80%
Set 2	2 × 75%	2 × 80%	2 × 85%	1 × 85%	1 × 75%	1 × 80%	1 × 90%	4 × 22%	4 × 22%	4 × 25%	4 × 25%	2 × 75%	2 × 80%	2 × 85%	1 × 85%
Set 3	1 × 80%	1 × 85%	1 × 90%		1 × 80%	1 × 85%		4 × 22%	4 × 25%	4 × 27%	4 × 30%	1 × 80%	1 × 85%	1 × 90%	
Set 4								4 × 25%	4 × 25%	4 × 27%					
Set 5								4 × 25%	4 × 27%	4 × 30%					
Sessions/wk	3	3	3	3	3	3	2	3	3	3	3	3	3	3	3

Abbreviation: RM, repetition maximum.

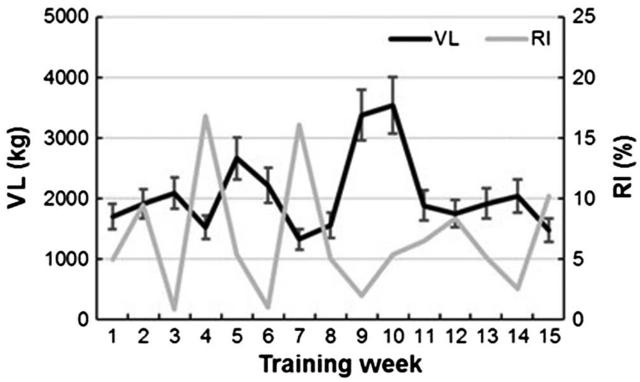

Figure 2 — Group average (mean [SD]) VL (in kg; solid black line) data and the RI (in %; dashed gray line) across 15 weeks of resistance training. RI indicates relative importance; VL, volume load.

Discussion

The large coefficients of determination and small RMSE indicate that the ANN developed in this study effectively modeled the association between VL and changes in CMJ height after 15 weeks of resistance training for male track-and-field athletes. The performance of the ANN was tested on 15 weeks of VL data from 4 separate athletes and suggested that the ANN could predict individual changes in CMJ height, with an average error between 0.21 and 1.47 cm. This finding agrees with other reports that showed ANN can be used to accurately predict Olympic swimming performance from the previous 4 weeks of training data.[8] While that report was only a single case study, the authors used multiple training cycles as input into their ANN. By contrast, the current study used data from more athletes, but only one training cycle. In addition, the inputs to the ANN in that study included weekly training volume for swim-related activities, resistance exercise, and dryland training, whereas in the current study, only resistance training VL was used as an input. Including the load of other training activities, such as plyometrics, would likely increase the utility of the ANN to help inform the training process.

One novel aspect to the current study is that we used an algorithm to determine the relative importance of the input variables in order to explain which input variables best predicted the output variable. This algorithm is based on the layer weights of the ANN and eliminates the so-called "black box" problem.[11] The connection weight algorithm suggested that VL of weeks 4, 7, and 15 have large (10%–17%) relative importance in predicting training-induced changes in CMJ height. It is interesting to note that all these weeks represent either deload or taper weeks, which suggests that planned reductions in VL are necessary to optimize changes in neuromuscular performance in response to resistance training.[5] Although not explicitly studied, cursory examination of data in another study suggests that an increase in SJ performance also occurred during a deload week.[5] These same authors also found significant cross-correlations between weekly training load and SJ data,[5] which supports findings from the current study that weekly VL is associated with longitudinal changes in CMJ performance.

Practical Applications

The developed ANN adequately modeled the relationship between weekly VL and its effects on CMJ performance. In addition, the ANN provided information about the relative importance of the VL from each week in predicting changes in CMJ height.

Conclusions

Artificial neural network can be used to model the association between weekly resistance training VL and changes in CMJ height. In addition, ANN can be used to gain insight into the relative contribution of weekly VL to changes in CMJ height. In the case of the current application of the ANN, the results showed that weeks with lower VL exhibited higher relative importance in explaining training-associated changes in CMJ performance across the competitive season.

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