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Section III – Sports Training

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Planning Training Loads for The 400 M Hurdles in Three-Month Mesocycles Using Artificial Neural Networks

by
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This paper presents a novel approach to planning training loads in hurdling using artificial neural networks. The neural models performed the task of generating loads for athletes' training for the 400 meters hurdles. All the models were calculated based on the training data of 21 Polish National Team hurdlers, aged 22.25 ± 1.96, competing between 1989 and 2012. The analysis included 144 training plans that represented different stages in the annual training cycle. The main contribution of this paper is to develop neural models for planning training loads for the entire career of a typical hurdler. In the models, 29 variables were used, where four characterized the runner and 25 described the training process. Two artificial neural networks were used: a multi-layer perceptron and a network with radial basis functions. To assess the quality of the models, the leave-one-out cross-validation method was used in which the Normalized Root Mean Squared Error was calculated. The analysis shows that the method generating the smallest error was the radial basis function network with nine neurons in the hidden layer. Most of the calculated training loads demonstrated a non-linear relationship across the entire competitive period. The resulting model can be used as a tool to assist a coach in planning training loads during a selected training period.

Key words: *400 m hurdles, training loads, artificial neural network.*

Introduction

A very important factor in achieving best competitive results in athletics is the selection of optimal training loads. The 400 m hurdle race is a complex athletic competition (McFarlane, 2000). To achieve an optimal performance level in this discipline, the athlete must have well developed coordination as well as the technique of running hurdles in a specific rhythm (Balsalobre-Fernández et al., 2013; Iskra and Cŏh, 2011). The complex nature of both motor and coordination characteristics of 400 meter hurdling requires the athlete to apply a variety of training loads, which are often radically different in their structure. The set of exercises for hurdlers running the 400 m includes typical exercises for sprinters (100-400 m), 110 m hurdlers, middle distance runners (800 m) and even long jumpers and triple jumpers. Hurdling research mainly concerns kinematics (Chow, 1998), physiology and biochemical variables (Kłapcińska et al., 2001; Ward-Smith, 1997) and the impact of external factors (e.g. wind) on performance (Quinn, 2010). Planning training loads is rarely discussed in the context of hurdling.

Planning the training process is very often carried out on the basis of practical experience of a coach, and lacks any scientific basis. As has been shown in previous studies on the best runners' training plans, performance improvement in hurdling is not always associated with an increase

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in the frequency and intensity of training (Iskra and Reguła, 2001). Sometimes overloading or poor balance between the types of training, results in a decrease in performance. This is therefore, of crucial importance to apply and verify different ways of selecting training loads.

Artificial intelligence methods play an important role in planning training loads. These include, among others, artificial neural networks (ANNs), which are developed from the design and function of the neural systems of living organisms (Bishop, 2006). Numerous studies have shown that the ANN is a means of predicting sports results which has a good predictive ability (Edelmann-Nusser et al., 2002; Przednowek and Wiktorowicz, 2011; Wilk et al., 2015). Thus, the ANN enables a coach to model the future level of athlete's performance and supports the process of sports selection (Maszczyk et al., 2012, 2013, 2016; Pfeiffer and Hohmann, 2012; Silva et al., 2007). Artificial neural networks are also widely used in the process of planning training loads (Maszczyk et al., 2016; Przednowek and Wiktorowicz, 2011; Przednowek et al., 2016; Roczniok et al., 2007; Ryguła, 2005). Another study has proposed the use of ANNs to classify kicking techniques (Lapkova et al., 2014). The aim of that paper was to examine the possibility to distinguish between two different kicking techniques from a kick impact force profile. ANNs are also used to analyze tactics in team sports (Perl et al., 2013; Pfeiffer and Perl, 2006). They allow a multi-dimensional analysis of training loads by creating a system which not only focuses on training that has been carried out, but also helps a coach choose appropriate training loads at a given stage of training. The solution presented in this study uses ANNs to generate training loads based on variables characterizing the athlete and his current results.

The main objective of this paper was to develop neural models for planning training loads for the entire career of a typical hurdler (with results from 69 to 61 s). The models were built using training data of high-level 400 m hurdlers. This system can therefore act as an additional tool in programming training loads for 400 m hurdlers.

Methods

The analysis included 21 Polish hurdlers aged 22.25 ± 1.96 competing from 1989 to 2012. The participants were high level athletes with average 400 m hurdles results of 51.26 ± 1.24 s. They were part of the Polish National Athletic Team Association representing Poland at the Olympic Games, as well as the World and European Championships in junior, youth and senior age categories. The best result over 400 m hurdles in the analyzed group equaled 48.19 s. Data on the study group are presented in Table 1.

The collected material allowed for the analysis of 144 training plans (mesocycles) applied in one of the three training periods. The first stage of training, i.e., the general preparation period (GPP), lasted from October to January; the second stage was the specific preparation period (SPP) from February to May and the third period included the competitive period (CP) running from June to September. There was also a transitional period, yet it was not analyzed in this study.

Planning training loads for 400 m hurdle runners considering the different training periods required a definition of the performance level as it was not possible to use 400 m hurdles testing tracks in each of the analyzed periods. The results of a 500 m flat run were therefore used to assess the fitness level in a selected period. In order to examine the relationship between the results over the 500 m distance and 400 m hurdles, a correlation coefficient was calculated for the results recorded in the competitive period. The obtained results confirmed that there was a strong correlation between the result in the races over 500 m and 400 m hurdles ($r_{xy} = 0.84$) with the statistical significance at the level of $\alpha = 0.001$ (Figure 1).

The generation of training loads (GT) is a complex and multidimensional (multiple-inputs and multiple-outputs) task. In the process of calculating the models, 29 variables were used. Table 2 contains the description of the variables and their basic statistics. Four variables describe the athlete (age, BMI, current result, expected result), while 25 variables refer to the completed training (three variables determine the training period and 22 variables concern training loads). It should be noted that some of the groups of training modalities are characterized by a high degree of dispersion ($V > 100\%$) (Table 2), because they were not considered in every stage of the annual cycle. An example could be runs over 1–3, 4–7 and 8–12 hurdles, which were not trained during the general preparation period. At the input of the GT model, the following variables were used: the expected result (x_1), characteristics of the athlete (x_2, x_3), the result of the participant (x_4) and variables representing the selected stage (x_5, x_6, x_7). At the output of the network there are neurons representing training loads (from y_1 to y_{22}) (Figure 2). The values appearing at outputs y_1–y_{22} represent the sum of all loads of that type, which should be implemented during the entire training period. Based on suggestions from the system, the coach should plan training loads to be carried out each day during the selected period.

In the analysis, Multilayer Perceptron (MLP) networks were used as well as Radial Basis Function (RBF) networks. MLP is the most popular type of network requiring iterative learning (Hastie et al., 2009). Learning of MLP networks was implemented by the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm using a hyperbolic tangent and exponential function as activation functions. The RBF network is characterized by the fact that the hidden neurons use radial basis functions (e.g. Gaussian function) as a function of activation (Bishop, 2006).

Another very important aspect is to specify the model variables to obtain the smallest errors while planning training loads. A major factor in selecting the validation method is the number of patterns, in this case, the number of accumulated training plans. The models presented in the paper were evaluated by LOOCV (leave-one-out cross-validation) (Arlot and Celisse, 2010). The idea of this method is based on the separation of n subsets of learning data from the data set where n is the number of all patterns. Each subset is formed by removing only one pair from the data set, which becomes the testing pair. A model is then calculated for each of the resulting subsets, thus obtaining its n versions evaluated by calculating the error for the remaining testing pair.

In this paper, the cross-validation error was expressed as a percentage and considered as a criterion for choosing the best model. Multi-dimensionality of the analyzed task may lead to incorrect conclusions while interpreting generalization errors. This is due to the fact that the outputs (training modalities) are represented on different scales and units which require normalization. The cross-validation error (CVE) is expressed by the formula:

$$NRMSE_k = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{ik}-\hat{y}_{-ik})^2}}{\max(y_k)-\min(y_k)} \cdot 100, \quad (1)$$

$$CVE = \frac{1}{r}\sum_{k=1}^{r} NRMSE_k \quad (2)$$

where: $NRMSE_k$ — normalized root mean square error for the k-th output, r — number of outputs, n — number of patterns, y_{ik} — real (measured) value, $\hat{y}_{-ik}$ — output value constructed in the i-th step of cross-validation based on a data set containing no testing pair (x_i, y_i), $\max(y_k)$ — maximum value of the k-th training load, $\min(y_k)$ — minimum value of the k-th training load.

For the implementation of the artificial neural network method, StatSoft STATISTICA software (StatSoft, 2011) was used and the cross-validation function was implemented using the Visual Basic language.

Results and Discussion

Determining the model

In order to determine the optimal architecture, three types of networks with neurons from 1 to 22 in the hidden layer were analyzed. The results of cross-validation in relation to the number of neurons in the hidden layer are presented in Figure 3. The best perceptron model with the 'tanh' function has eight neurons in the hidden layer ($CVE = 14.4\%$), while the best network with the 'exp' function has three hidden neurons ($CVE = 14.6\%$). The best RBF model has cross-validation error equal to 14.1%. After comparing the obtained errors, the RBF network consisting of seven inputs, nine neurons in the hidden layer and 22 outputs (structure: 7-9-22), was chosen. It should be noted that the use of a larger number of neurons in the hidden layer results in a rapid increase in generalization errors, and thus the generated loads will be inaccurate and impossible to implement. Figure 4 shows the error values generated by the outputs of the best network. Detailed analysis of the chosen model showed that the biggest error appeared for explosive strength of the upper limbs (20.27%) and in technical exercises of walking pace (23.51%). The smallest error characterized the outputs representing speed endurance (7.37%) and upper body strength (7.11%).

Generating training loads

Figures 5–8 present the results of generating training loads using an RBF network for a hypothetical athlete who is 21 years old and has a BMI of 22 kg/m². The goal of training was to improve the result over 500 m by one second. As an output result, the score from 69 to 61 s was chosen, which reflected the entire career of a typical hurdler. The training loads considered were categorized into five groups: 'speed', 'endurance', 'strength endurance', 'strength', and 'technique and rhythm' (Table 2).

Speed The 400 m hurdle race is a sprint race, thus speed plays a significant role in preparing a hurdler for this distance (Iskra, 2014; McFarlane, 2000). While considering training loads influencing the speed of the race (y_1, y_2, y_3), it may be noted that the greatest changes occurred during the SPP (Figure 5). The number of exercises applied to develop race speed (y_1) and technical speed exercises (y_2) steadily increased until the athlete achieved the result of 66 s.

It is seen that at higher competitive levels, the number of exercises such as running at maximal and sub-maximal intensity should be increased. It may be assumed that during GPPs, the level of these training loads does not change significantly. This is closely related to training needs specific for this period (the initial training period) and weather conditions prevailing in Poland in this particular time (the winter period). At this time, speed training is mostly oriented towards specific exercises (y_3). It is also worth noting that the training load is similar regardless of the competitive level of the hurdler.

Endurance Another group of training loads included exercises for developing endurance (y_4–y_7). On the basis of the results, it can be stated that the greatest increase in endurance loads occurred during the SPP (Figures 5 and 6). By analyzing speed endurance (y_4), it can be seen that this load had the lowest value during the GPP, and it did not change significantly when the hurdler's skill increased. However, in the SPP it increased slightly once the hurdler achieved the result of 64 s. This value can be defined as the point at which the hurdler reaches a high level. The opposite situation may be observed for the CP, when speed endurance began to decrease (from 66 s). The specific (anaerobic) endurance (y_5), which is very important in this event, is characterized by a steady increase in all periods of a hurdler's career. This kind of endurance is crucial to achieving success in the 400 m hurdles (Iskra, 2014). In the GPP and CP, both pace endurance (y_6) and aerobic endurance (y_7) have the same shape, yet y_7 is greater than y_6. These loads can be classified as complementary training.

Table 1

Basic statistics of the analyzed group of athletes

Variable	$\bar{x}$	min	max	sd	V (%)
Age (years)	22.25	19	27	1.96	8.81
Body height (cm)	185.0	177	192	4.67	2.52
Body weight (kg)	74.29	69	82	2.69	3.62
BMI (kg/m²)	21.72	19.67	24.07	1.02	4.69
Result on 400 m hurdles (s)	51.26	48.19	53.60	1.23	2.41

Table 2

Description of variables used to construct the models

Variable Inputs	Description	$\bar{x}$	min	max	sd	V (%)
x_1	Expected 500 m sprint (s)	65.2	60.9	71.2	2.1	3.2
x_2	Age (years)	22.3	19.0	27.0	2.0	8.8
x_3	Body mass index	21.7	19.7	24.1	1.0	4.7
x_4	Current 500 m sprint (s)	66.4	61.5	72.1	2.0	3.0
x_5	The general preparation period	—	—	—	—	—
x_6	The specific preparation period	—	—	—	—	—
x_7	The competitive period	—	—	—	—	—
Outputs — speed						
y_1	Maximal speed (m)	1395	0	4300	798	57.3
y_2	Technical speed (m)	1748	0	7550	1293	74.0
y_3	Technical and speed exercises (m)	1417.8	0	5100	840	59.2
Outputs — endurance						
y_4	Speed endurance (m)	4218	0	93670	7984	189.3
y_5	Specific hurdle endurance (m)	4229	0	13700	2304	54.5
y_6	Pace runs (m)	54599	0	211400	37070	67.9
y_7	Aerobic endurance (m)	121085	4800	442100	75661	62.5
Outputs — strength endurance						
y_8	Strength endurance I (m)	8690	0	31300	6806	78.3
y_9	Strength endurance II (amount)	1999	0	21350	2616	130.8
Outputs — strength						
y_{10}	General strength of lower limbs (kg)	41353	0	216100	35565	86.0
y_{11}	Directed strength of lower limbs (kg)	19460	0	72600	12540	64.4
y_{12}	Specific strength of lower limbs (kg)	13887	0	156650	16096	115.9
y_{13}	Trunk strength (amount)	15480	0	200000	21921	141.6
y_{14}	Upper body strength (kg)	1101.9	0	24960	2121	192.5
y_{15}	Explosive strength of lower limbs (amount)	274.7	0	1203	190	69.3
y_{16}	Explosive strength of upper limbs (amount)	147.9	0	520	116	78.5
Outputs — technique and rhythm						
y_{17}	Technical exercises – walking pace (min)	141.6	0	420	109	77.5
y_{18}	Technical exercises – running pace (min)	172.9	0	920	135	78.4
y_{19}	Runs over 1-3 hurdles (amount)	31.9	0	148	30	95.0
y_{20}	Runs over 4-7 hurdles (amount)	56.5	0	188	51	91.3
y_{21}	Runs over 8-12 hurdles (amount)	50.5	0	232	52	104.3
y_{22}	Hurdle runs in varied rhythm (amount)	285.7	0	1020	208	73.0

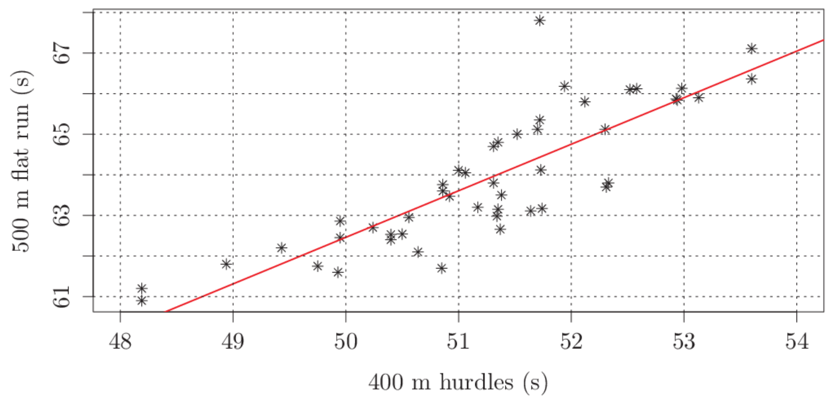

Figure 1
Chart of correlation between the 400 m hurdles and 500 m flat run

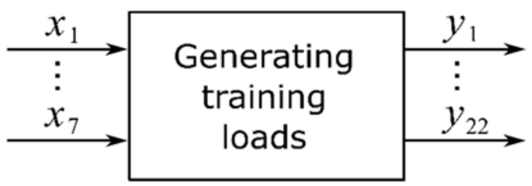

Figure 2
Block diagram for training loads generated for 400 m hurdle races

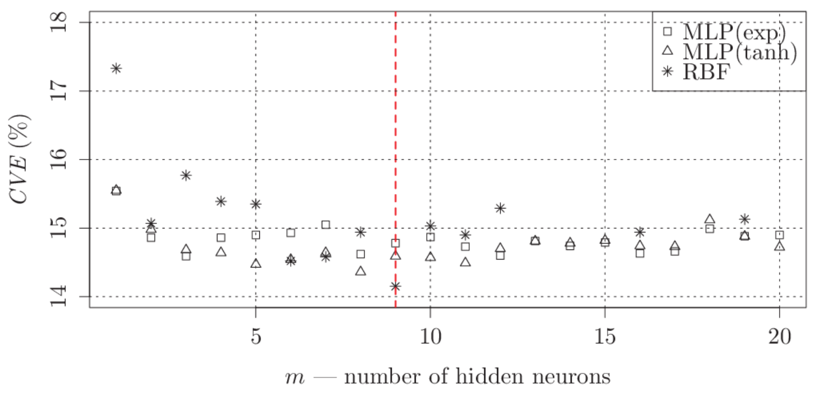

Figure 3
Cross-validation error (CVE) for ANN in relation to the number of hidden neurons; vertical line drawn for m = 9 signifies the number of hidden neurons chosen in cross-validation

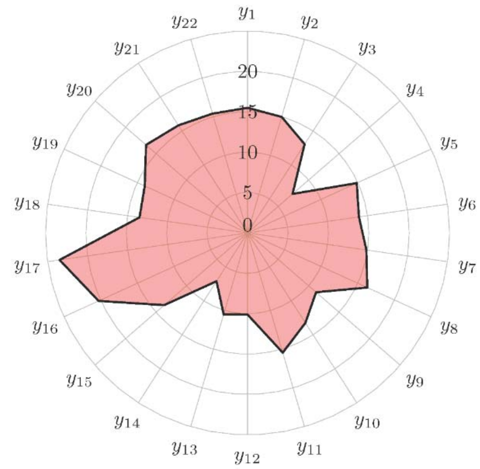

Figure 4
Errors of the outputs (in percentage) for the RBF network used to generate training loads

Table 3

Indications for a coach for different periods (results in s)

Period	GPP	SPP	CP	GPP	SPP	CP	GPP	SPP	CP
Current result		68			64			61	
Expected result		67			63			60	
Speed									
y_1	→	↓	↓	→	↑	→	↑	→	→
y_2	→	↓	↓	→	↑	→	↑	→	↑
y_3	→	↓	→	→	↑	→	→	↑	→
Endurance									
y_4	→	→	→	→	↑	→	→	→	↓
y_5	→	→	→	→	↑	→	→	→	→
y_6	→	→	↓	→	↑	→	→	→	↑
y_7	→	→	→	→	↓	→	→	→	→
Strength endurance									
y_8	→	↑	↑	→	↓	→	↓	↓	↓
y_9	→	↑	↑	→	↓	→	↓	↑	↓
Strength									
y_{10}	→	↑	↑	→	↓	→	↓	↑	→
y_{11}	→	↑	→	→	↓	→	→	→	→
y_{12}	→	↑	→	→	↓	→	→	↑	→
y_{13}	→	↑	↑	→	↓	→	↓	→	↓
y_{14}	→	→	→	→	↓	→	→	↑	↓
y_{15}	→	→	→	→	↑	→	↑	↓	→
y_{16}	→	↓	→	→	↑	→	→	→	→
Technique and rhythm									
y_{17}	→	↑	→	→	→	→	→	↓	→
y_{18}	→	→	→	→	↓	→	→	→	→
y_{19}	→	→	→	↑	→	→	↑	↑	→
y_{20}	→	↑	→	↑	→	→	↑	→	→
y_{21}	→	↑	→	↑	→	↑	↑	→	→
y_{22}	→	↓	↓	→	↑	→	→	→	↑

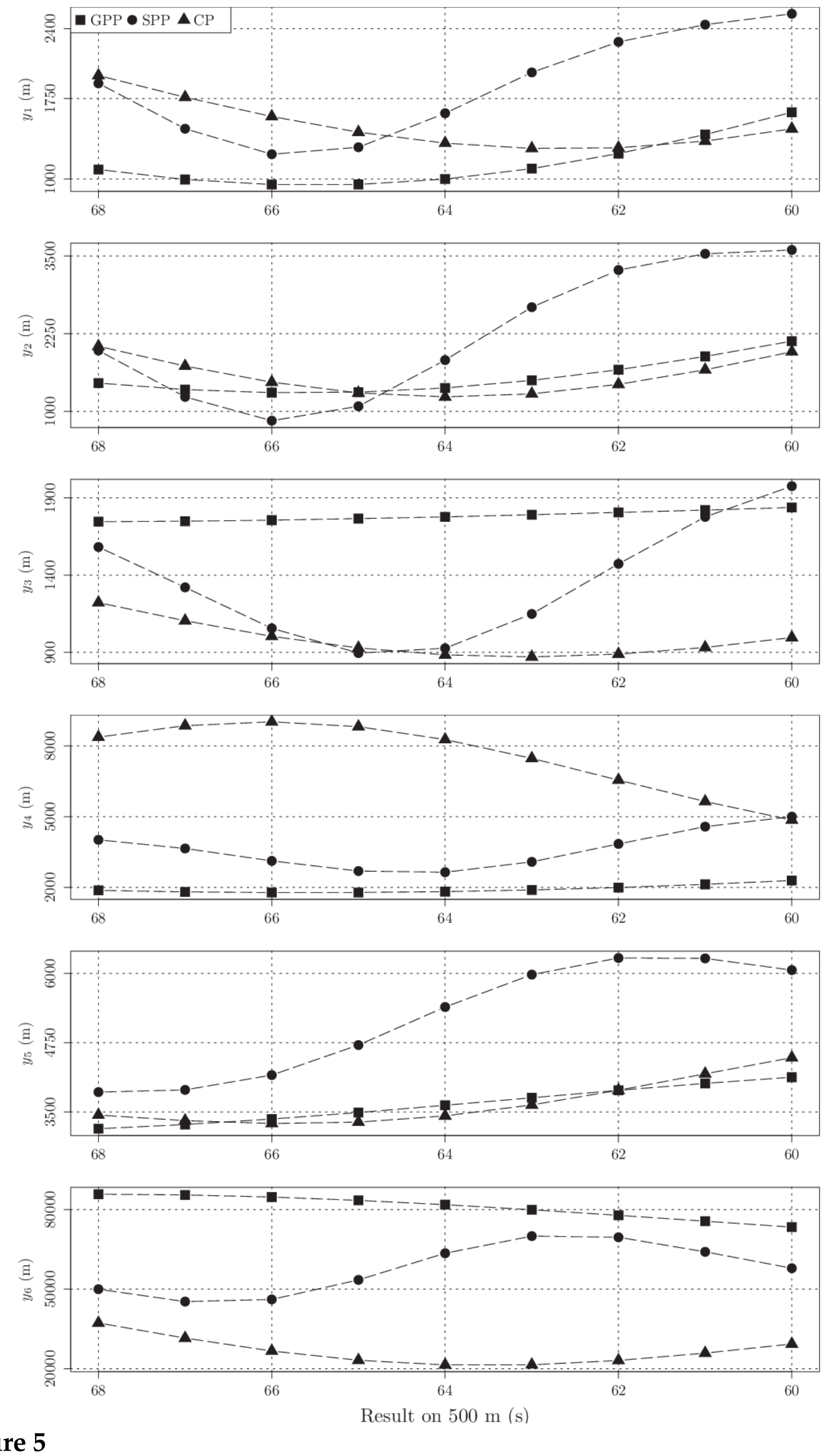

Figure 5

Training loads $y_1 - y_6$ generated for results from 68 to 60 s

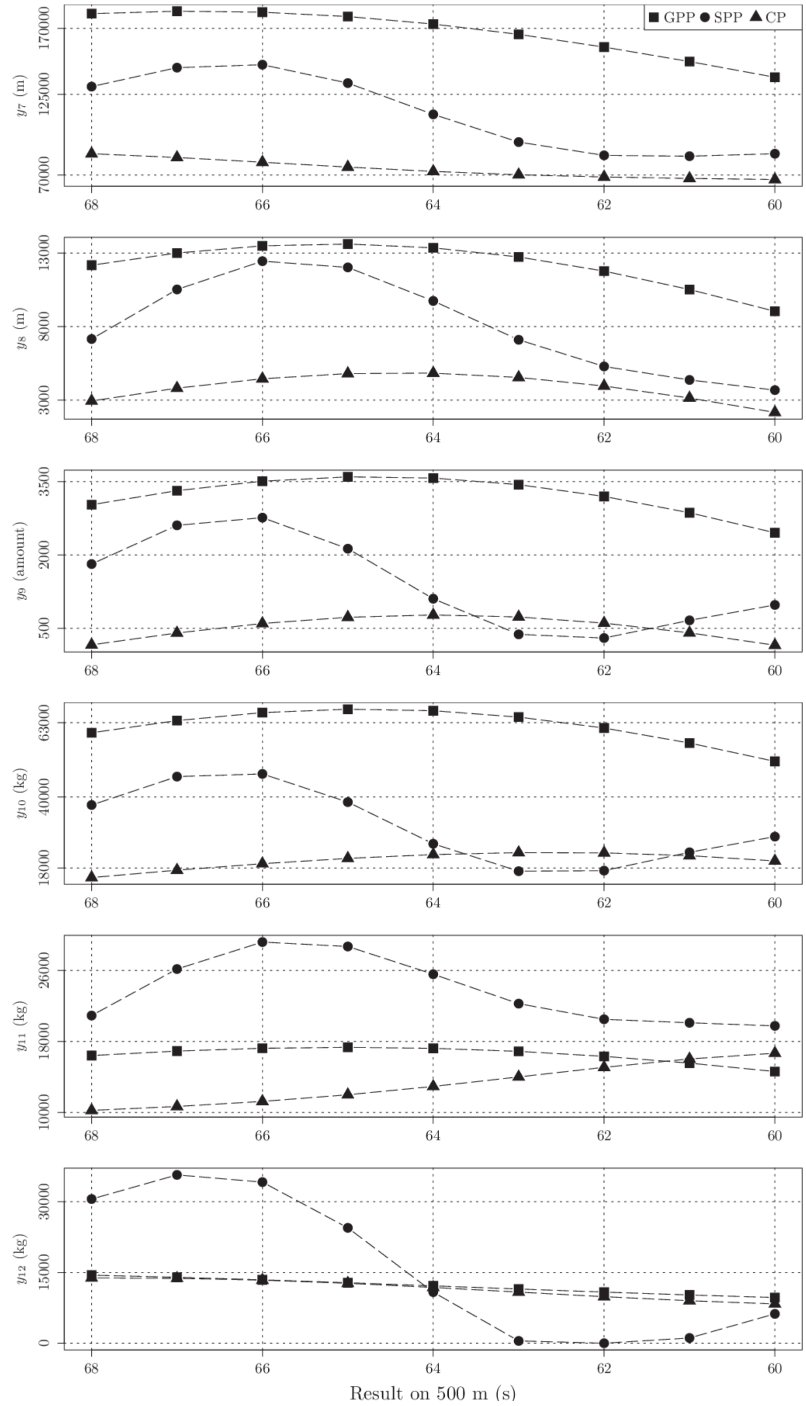

Figure 6

Training loads $y_7 - y_{12}$ generated for results from 68 to 60 s

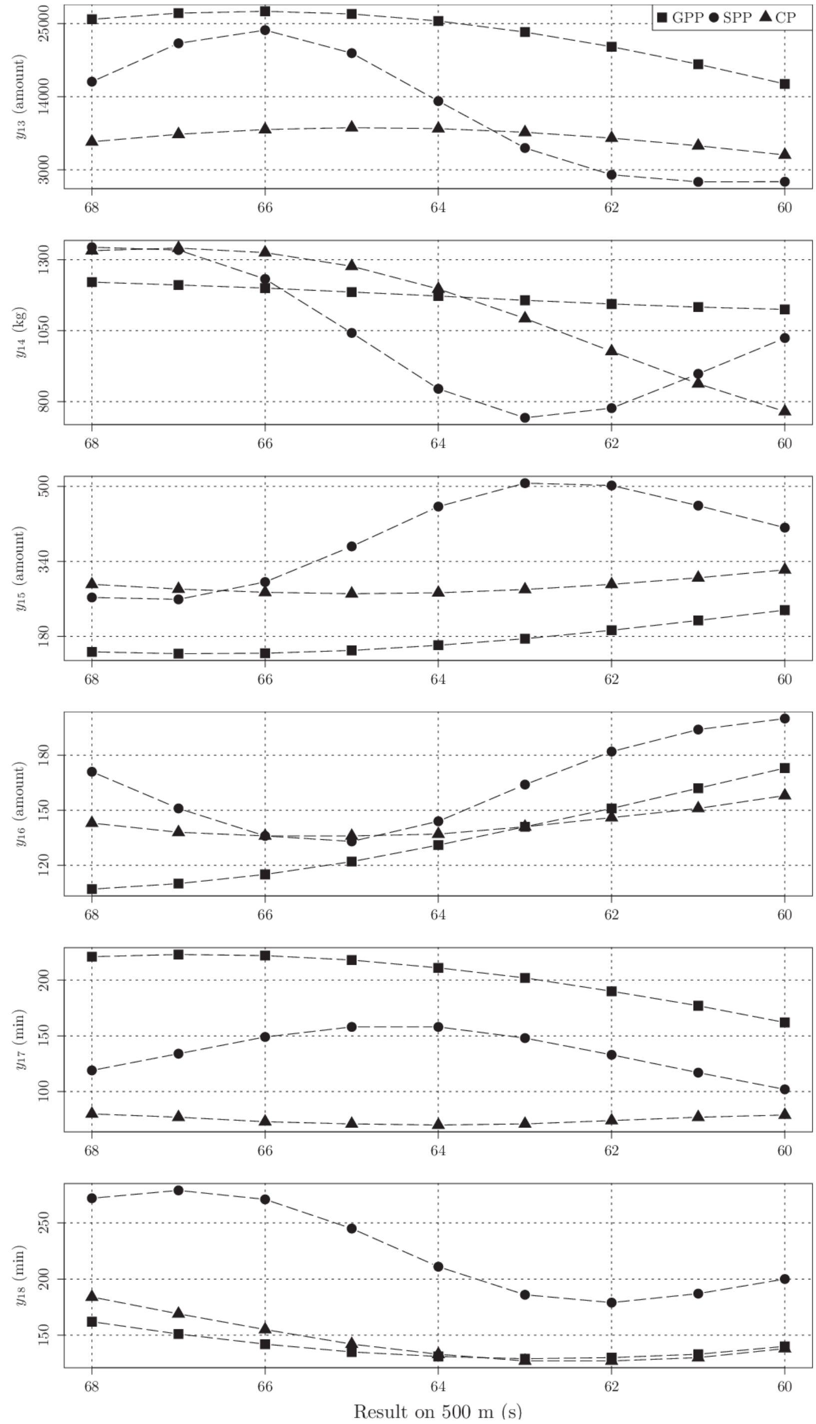

Figure 7

Training loads $y_{13} - y_{18}$ generated for results from 68 to 60 s

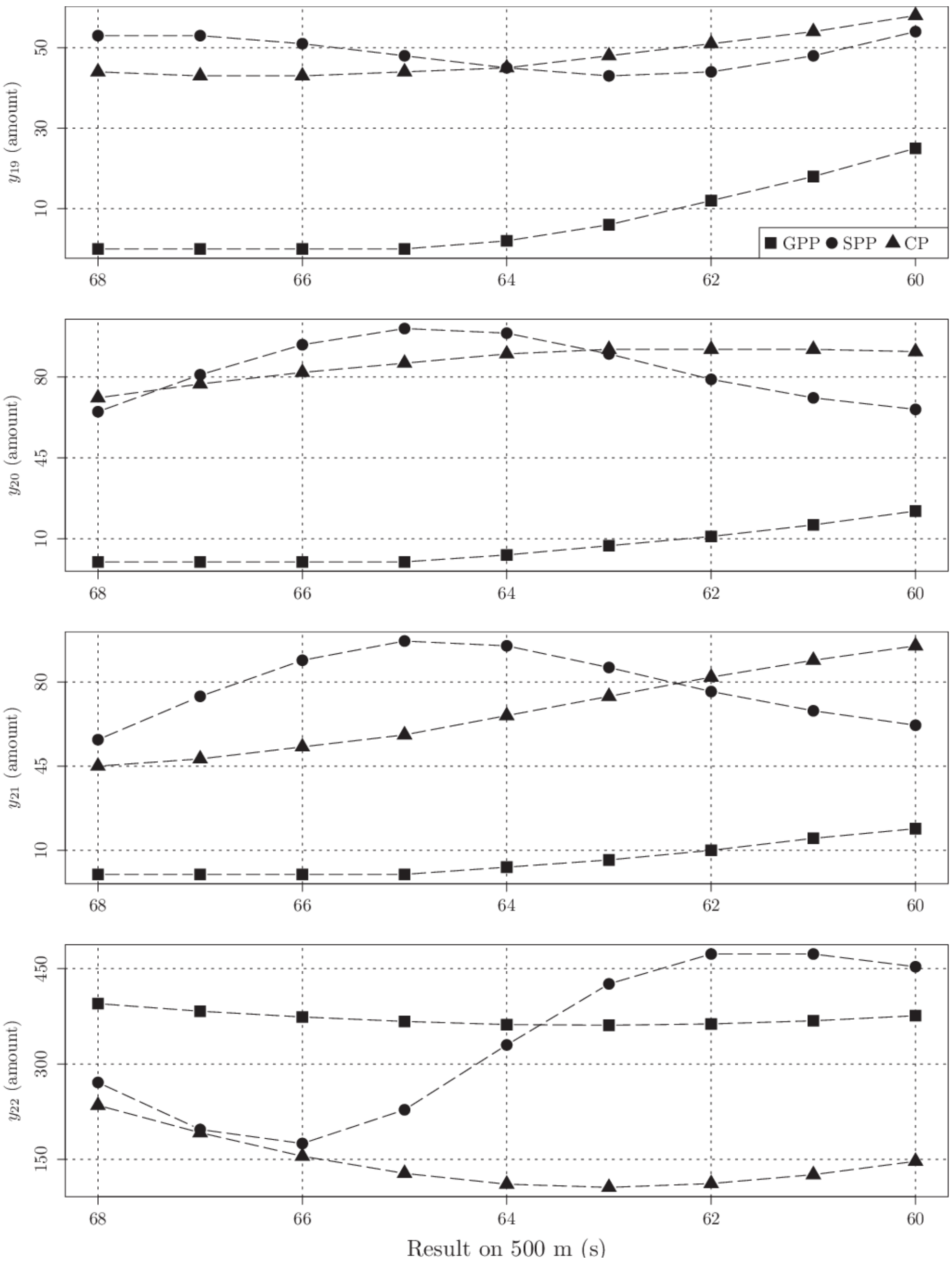

Figure 8

Training loads $y_{19} - y_{22}$ generated for results from 68 to 60 s

Strength endurance Strength endurance is developed by two training modalities. The first includes running exercises: ascents, skipping for more than 80 m and running with resistance (y_8); the second includes jumping exercises in the form of multihops over a distance of more than 30 m (y_9). As can be seen in Figure 6, changes in both variables are very similar. In the GPP, the amount of training was greatest and reached its peak when the hurdler achieved 64–65 s. It is also characteristic that in the SPP (below 66 s), the amount of training either decreased or slightly increased as better results were achieved. During this period, training for strength endurance consisted of higher intensity exercises. Basically, during the CP, the load was almost constant with a slight increase when the athlete achieved the results ~64 s.

Strength The largest group of training modalities includes exercises ($y_{10}-y_{16}$) for developing muscle strength (Figures 6 and 7). Proper strength training of the lower extremities is particularly important while training a hurdler. In the training loads y_{10}, y_{11} and y_{12}, the non-linearity in the SPP may be noticed. The y_{10}— y_{11} loads in a competitor's early career are followed by an increase in training volume, until the hurdler achieves 66–67 s. As the athlete's performance level increases, the number of these exercises decreases. These changes in training volume relate to specific strength (y_{12}), which is relevant in hurdlers' training only to the moment of achieving the result of 63 s.

While analyzing the abdominal and back muscles (y_{13}), it can be noted that the majority of these exercises are carried out during the GPP, throughout an athlete's career. Changes of loads to arm and shoulder-rim muscles have different characteristics (y_{14}). These loads do not change significantly in the GPP. However, in the SPP there is a gradual decrease until the athlete achieves the result of 63 s, followed by a slight increase when a hurdler reaches their peak performance. As the hurdler's competitive level increases, the number of exercises during the CP decreases until the end of their career.

Changes in the number of strength-speed exercises for the lower limbs (y_{15}) during the GPP and CP are small throughout a hurdler's career. It is worth noting that during the SPP the number of dynamic strength exercises gradually increases until the athlete achieves the result of 63 s and thereafter, it is reduced slightly.

It can also be observed that speed and strength exercises for the upper limbs (y_{16}) are characterized by an increase in their number in each training period throughout an athlete's career (except for those at a low results level (from 68 to 66 s)).

Technique and rhythm The final group of training loads concerns exercises which develop technique and rhythm ($y_{17}-y_{22}$ in Figures 7 and 8). The smallest changes to the loads can be observed for technical exercises performed while walking (y_{17}). It should be noted, however, that for every fitness level (from 68 to 60 s), the largest number of these exercises is used during the GPP. This is fully understandable, because these exercises can be performed in indoor conditions during the winter months. In contrast, when considering technical exercises (y_{18}), greatest volume of these exercises is observed during the SPP. In the remaining periods the change of y_{17} and y_{18} loads is not significant.

The analysis shows that running 1–3 hurdles (y_{19}) and 4–7 hurdles (y_{20}) is very similar throughout the hurdler's career. The majority of the load is carried out during the SPP and CP. During the GPP, loading is lowest, but it is worth noting that at the elite level (from 63 s), athletes also perform such training during the GPP.

Of paramount importance for training for the 400 m hurdles are hurdling exercises performed over 8-12 hurdles (y_{21}). The analysis shows that loading is very small during the GPP (lack of conditions at the track) and that most of this training is carried out during the SPP and CP. It is noticeable that the higher the level of an athlete, the greater loading in the CP. In addition, hurdlers should also run hurdles in different rhythms. The analysis indicates that the performance level does not affect the variable y_{22} in the GPP. Another situation is observed during the SPP where y_{22} decreases slightly (at its lowest at 66 s), then rises to its maximum when the hurdler achieves 62 s, and finally stabilizes when the athlete achieves peak performance.

Using the model in practice

The calculated model can be used in different ways. For example, if one assume that the current result (x_4) of a selected athlete is equal to 64 s, using the presented neural model this result should be improved by one second, that is 63 s. The generation of training loads for a given period can be carried out as follows:

1. for the GPP, the input vector has the following form:

$$\mathbf{x} = [x_1, \dots, x_7] = [63, 21, 22, 64, 1, 0, 0], \quad (3)$$

for which the output vector generated by the model is:

$$\mathbf{y} = [y_1, \dots, y_{22}] = [1097, 1500, 1791, 1892, 3755, 79932, 165888, 12732, 3438, 64710, 16889, 11494, 23734, 1157, 175, 141, 202, 129, 6, 7, 6, 361]. \quad (4)$$

The elements of the vector $\mathbf{y}$ mean that the suggested training consists of the following loads. In the group of speed loads the athlete should run 1097 m at maximum intensity (y_1), 1500 m at submaximal intensity (y_2) and cover 1791 m performing specific sprint exercises i.e., skipping and multiple jumps (y_3). In the group of strength loads, the following values are proposed: 1892 m of running at maximal and submaximal intensity for 80 — 150 m (y_4), 3755 m of running at maximal and submaximal intensity for 150 — 500 m (y_5), 79932 m of running at high and moderate intensity for 150 — 800 m (y_6) and 165888 m of continuous running (y_7). For strength endurance training, 12732 m of run-ups and runs with resistance (y_8) and 3438 multi-jumps above 30 m (y_9) are proposed. For strength training, the athlete should perform squats with a total load of 64710 kg (y_{10}), half squats with a total load of 16889 kg (y_{11}), weighted jumps with a total load of 11494 kg (y_{12}), core stability exercises with a total load of 23734 kg (y_{13}), upper body exercises with a total load of 1157 kg (y_{14}), 175 multi-jumps up to 30 m (y_{15}) and 141 shot put throws (y_{16}). The proposed training for technique and rhythm includes 202 min of specific exercises with hurdles performed while marching (y_{17}), 129 min of specific exercises with hurdles performed while running (y_{18}), 6 runs over 1–3 hurdles (y_{19}), 7 runs over 4–7 hurdles (y_{20}), 6 runs over 8–12 hurdles (y_{21}) and 361 runs over hurdles in a varied rhythm (y_{22}).

2. for the SPP, the input vector has the following form:

$$\mathbf{x} = [x_1, \dots, x_7] = [63, 21, 22, 64, 0, 1, 0], \quad (5)$$

for which the output vector generated by the model is:

$$\mathbf{y} = [y_1, \dots, y_{22}] = [1992, 2676, 1149, 3084, 5977, 69998, 92455, 7101, 375, 17002, 22258, 490, 6280, 743, 507, 164, 148, 186, 43, 90, 86, 426]. \quad (6)$$

The interpretation of elements of the vector $\mathbf{y}$ is the same as for the GPP.

3. for the CP, the input vector has the following form:

$$\mathbf{x} = [x_1, \dots, x_7] = [63, 21, 22, 64, 0, 0, 1], \quad (7)$$

for which the output vector generated by the model is:

$$\mathbf{y} = [y_1, \dots, y_{22}] = [1285, 1284, 871, 7473, 3626, 21500, 70183, 4543, 731, 22752, 14010, 10839, 8647, 1093, 280, 141, 71, 127, 48, 92, 74, 106]. \quad (8)$$

The interpretation of elements of the vector $\mathbf{y}$ is the same as the GPP and SPP.

Another approach considers using less detailed information calculated by the model. For example, we can observe trends of training loads at different competitive levels. In Table 3, the trends for three selected cases are presented. These cases represent athletes at low, medium and high competitive levels. The trends are calculated by the following formula:

$$\delta_i = \frac{y_i^{t+1} - y_i^t}{y_i^t} \cdot 100, \quad (9)$$

where: y_i^t — current training load, y_i^{t+1} — generated training load, $i = 1, \dots, 22$ — number of training loads. Using the trends δ_i, we can formulate an approximate proposition of a training program for a coach. Equation (9) allows trends to be determined, assuming improvement of the outcome by one second. In Table 3, the symbols mean: → — training load should stay at the same level ($\delta_i \in [-10\%, 10\%]$), ↓ — training load should decrease ($\delta_i < -10\%$) and ↑ — training load should increase ($\delta_i > 10\%$).

The calculated trends show that in the GPP for beginner and intermediate-advanced athletes, there are no significant changes of training loads. Exceptions include loads shaping technique and rhythm, which are increased for an intermediate athlete. At the elite performance level in the GPP, there are changes in all the groups except the endurance load which remains at the same level. In the SPP, most of the training loads change at every level of the event. It is noteworthy that the training load developing the strength of both a beginner and an advanced competitor does not change. Analyzing the trend in the CP, it can be seen that some changes occur only in beginners and elite athletes. Basically, it can be concluded that for an intermediate competitor, the value of training loads does not change. Relatively small changes occur in loads during the CP in the group forming technique and rhythm.

Conclusions

In this paper, a novel approach for planning training loads in hurdling using neural models was presented. The best model was the RBF network with nine neurons in the hidden layer. This model generates the cross-validation error equal to 14%. All training loads are characterized by the fact that an athlete with a fitness level similar to the analyzed level is able to carry out the suggested training program. Using the calculated model in practice may be of great importance for coaches as it can support the selection of appropriate training loads and intensity.

The limitations of the presented approach are connected with using results in practice, because the generated training data should be only treated as a suggestion for the coach who should perform necessary adjustments in order to adapt it for a particular athlete. Moreover, using these models requires specific software to program training loads. Therefore, further work should focus on building an interface for the athlete and coach, which will allow for the implementation of the proposed solution to planning training loads. Other areas for future research to be considered include generating training load values using different methods of machine learning.

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