# Planning Training Loads to Develop Technique and Rhythm in the 400 m Hurdles using RBF Network

Krzysztof Przednowek[1], Janusz Iskra[2], Stanislaw Cieszkowski[1] and Karolina H. Przednowek[1]
[1]*Faculty of Physical Education, University of Rzeszow, Rzeszow, Poland*
[2]*Faculty of Physical Education and Physiotherapy, Opole University of Technology, Opole, Poland*

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Abstract: In this paper training loads to develop technique and rhythm in hurdles are presented. The training loads were generated using an artificial neural networks model with radial basis functions. The analysis included 21 hurdlers who were members of the Polish National Team. The calculations for the neural model were made using 48 training programmes. The evaluation of the models was carried out using the cross-validation method. Five independent variables (age, body height, body weight, current result and expected result) and four dependent variables representing the selected training loads were analyzed. The determined model generated training loads with an error of approximately 21%. Experimental results showed the training programme for a hypothetical athlete. The analysis shows that all the examined training loads are of a non-linear nature. The proposed solution can be used as a tool to support planning for selected training loads in 400 m hurdles.

## 1 INTRODUCTION

Hurdles races are complex athletic events since they require both motor and technical skills. The results achieved in these races depend on the level of strength, the jumping technique and the so-called hurdle rhythm (McFarlane, 2000). In the 400 m hurdles technique plays an exceptional role. The use of appropriate technical skills while taking off, jumping over the hurdle and landing, is very important. The 400 m hurdles technique is usually referred to as that of jumping 10 hurdles, each 91.4 cm high. It includes the individual stages of the race, i.e. start, racing to the first hurdle, racing through the hurdles and racing to the finish line. Hurdling, and strictly speaking jumping over the hurdle, is a form of complex, dynamic motion, described in studies as a classic example of using the laws of physics in sport (Iskra, 2012).

The evaluation of race technique comes down to the biomechanical assessment of each individual component (Čoh et al., 2008). In the course of biomechanical analysis, errors in movement are discovered and can be subsequently corrected by means of an appropriate training plan. While planning the training loads, the coach very often relies exclusively on his own expertise. Such an approach sometimes lacks scientific basis. It is therefore necessary to look for solutions that would support the planning of training loads. One such solution may be the application of advanced mathematical models (Maszczyk et al., 2014; Wiktorowicz et al., 2015). Using these techniques leads to a better understanding of the subject under consideration. The most commonly used methods of mathematical support for the process of sports training include artificial neural networks (Ryguła, 2005; Pfeiffer and Perl, 2006; Perl et al., 2013; Silva et al., 2007). In sports science neural models are widely used for modelling, prediction and optimization. These models make it possible to predict sporting talent (Roczniok et al., 2007) or determine the impact of the training on the result achieved (Przednowek et al., 2014). In this study we therefore, decided to use artificial neural networks in planning the training loads to develop technique and rhythm.

A novel approach to planning training loads developed by the authors, is the construction of model-generated training loads using selected parameters characterizing the athlete and his current results. This supports the planned training programme in the training period under consideration (special preparation period). The main purpose of this study is the construction of artificial neural networks to generate the training loads to develop selected technique components in a 400 m hurdles race. The construction of the model was based on training data from athletes with a high level of fitness.



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# 2 MATERIAL AND METHODS

## 2.1 Training Data

The training data used for the construction of the training planning model were taken from athletes competing at a high level. The analysis included 21 Polish hurdlers who were members of the Polish National Team and represented Poland at Olympic Games, and European and World Championships. The 48 training programmes carried out during the special preparation period were selected. Additionally the results before and after the analyzed training period were registered. The special preparation period usually lasts about three months (from February to May). Five independent variables ($x_1$ – age, $x_2$ – body height, $x_3$ – body weight, $x_4$ – current result, $x_5$ – expected result) and four dependent variables ($y_1$, $y_2$, $y_3$, $y_4$) representing the training loads were analyzed. A training load is the work or exercise that an athlete performs during a training session. The selected training loads are those loads which make up technique and rhythm (Tab. 1). The values of these training loads are measured in a number of races. The basic statistic ($\bar{x}$ – mean value, *min* – minimum, *max* – maximum, *sd* - standard deviation) of the variables used to calculate the model are presented in Table 1.

Due to the difficulties connected with carrying out the test in 400 m hurdles races during the special preparation period (winter), the athletes ran a 500 m test race (flat run). As demonstrated in the previous study, the result of a 500 m race reflect the hurdler's current performance in a 400 m race (Alejo, 1993; Przednowek et al., 2014). In this study, the 500 m flat run was adopted as an indicator of fitness level.

## 2.2 The Idea of Supporting the Training Process

The proposed method to support the training process involves the use of a mathematical model to generate training loads with given input parameters (independent variables). The coach using the model inputs age, body weight and body height statistics for the competitor (Fig. 1). At this stage his current result for the 500 m race is entered, which reflects his current physical condition and the result expected. At the output stage of the model the values of the training loads are generated (Fig. 1). The loads thus generated constitute a training plan to prepare the hurdler for the special preparation period. The values appearing at outputs $y_1$–$y_4$ represent the sum of all loads of that type, which should be implemented during the entire training period. Based on the suggestions from the system, the coach plans the training loads to be carried out each day during the special preparation period.

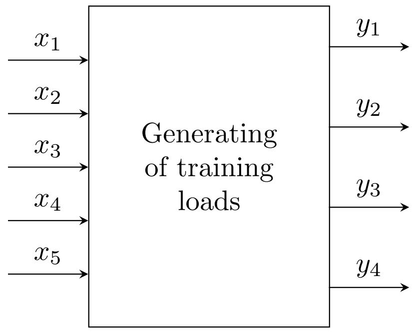


Figure 1: Block diagram of models generating training loads.

## 2.3 Calculating and Evaluating Method

In the conducted analysis, the model of an artificial neural network with radial basis functions (RBF) was applied (Bishop, 2006). Networks with a radial basis functions have one hidden layer, composed of radial neurons and an output layer consisting of linear neurons. The RBF networks were implemented using the Statistica 10 software (StatSoft, Inc., 2011). In the process of finding the best model, networks with various numbers of neurons in the hidden layer (from 0 to 10) were analyzed. During the evaluation of the neural network, the leave-one-out cross-validation method was used (James et al., 2013); cross-validation error was defined as:

$$CV_j = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{ij} - \hat{y}_{-ij})^2}}{\max(y_j) - \min(y_j)} \cdot 100, \qquad (1)$$

where: $n$ – number of patterns (48), $y_{ij}$ – real value, $\hat{y}_{-ij}$ – the output value constructed in $i$–th step of cross-validation based on a data set containing no testing pair ($x_i$,$y_i$), $CV_j$ – cross validation error for $j$–th output. The main criterion for model selection was the arithmetic error average, calculated for all network outputs. The cross-validation was implemented using Visual Basic language.

# 3 RESULTS

The research results are demonstrated in two sections. In the first one, the model calculation is presented, while in the second section the generated training loads are analyzed.

Table 1: Description of the variables.

| Variable | Description | $\bar{x}$ | *min* | *max* | *sd* |
|---|---|---|---|---|---|
| $x_1$ | Expected results on 500 m run (s) | 65.06 | 61.50 | 69.10 | 1.80 |
| $x_2$ | Age (years) | 22.25 | 19.00 | 27.00 | 1.97 |
| $x_3$ | Body height (cm) | 185.04 | 177.00 | 192.00 | 4.70 |
| $x_4$ | Body weight (kg) | 74.29 | 69.00 | 82.00 | 2.71 |
| $x_5$ | Current results on 500 m run (s) | 66.78 | 62.50 | 71.15 | 1.68 |
| $y_1$ | Runs over 1–3 hurdles (amount) | 46.40 | 3.00 | 148.00 | 28.87 |
| $y_2$ | Runs over 4–7 hurdles(amount) | 82.38 | 4.00 | 176.00 | 40.23 |
| $y_3$ | Runs over 8–12 hurdles (amount) | 79.71 | 0.00 | 194.00 | 45.83 |
| $y_4$ | Hurdle runs in varied rhythm (amount) | 330.02 | 0.00 | 745.00 | 156.35 |

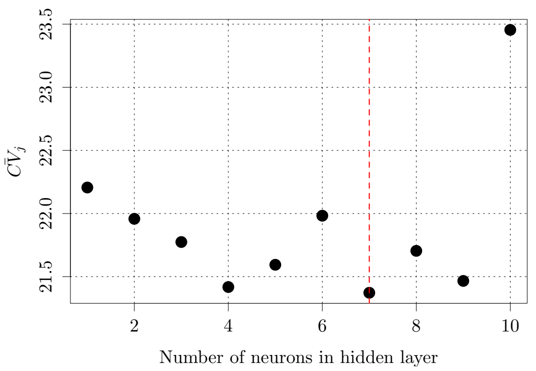


Figure 2: Mean cross-validation errors; The X-axis represents the number of neurons in the hidden layer of RBF network which range from 1 to 10. The Y-axis represents the mean value of $CV_j$ error for all outputs.

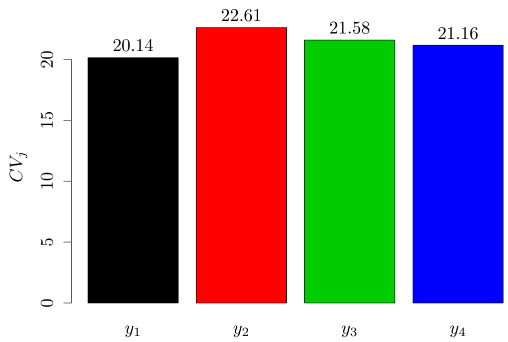


Figure 3: Cross-validation errors $CV_j$ of each output.

## 3.1 Model Calculation

In order to determine the network featuring the best generalization ability, a cross-validation was performed. Networks with hidden neurons from 1 to 10 were examined. The cross-validation results are presented in Figure 2.

The conducted analysis shows that the best model is the artificial neural network with seven neurons in the hidden layer. That network generates an average cross-validation error of 21%. Errors generated by individual network outputs are presented in Figure 3. Output $y_1$ is characterized by the smallest generalization error (20.14%), while the $y_2$ output features the largest error (22.61%).

## 3.2 Generation of Training Loads

The next step in the analysis was to calculate the training loads using the selected RBF network. On the network input, the data from a hypothetical athlete (age 21, body height 185 cm, weight 75 kg) were entered. Loads were generated on the assumption that the 500 m race results would be improved by one second, taking as the output result, results from 68 s to 62 s, respectively. The range of result from 68 s to 62 s reflects the career of a hurdler. The results of this experiment are presented in Figure 4. The graphs show loads generated in such a way that the Y-axis represents the level of training loads while the X-axis is the expected result. The values on the X-axis are placed in descending order as the increase in the competitors' sports level is associated with a decrease in the time they achieve over a specified distance. For example, if a competitor wants to improve his result from 66 s to 65 s then the generated training plan indicates that the competitor should implement a workout with the following capacity: $y_1 = 54$; $y_2 = 91$; $y_3 = 87$ and $y_4 = 225$.

The analysis of training loads generated for hypothetical athletes shows that all the examined loads are of non-linear nature (Fig. 4). Considering the values calculated for $y_1$ (Fig. 4(a)), it should be noted that as well as the achievement of better results, the volume of the loads increases. The maximum value of $y_1$ is observed when the athlete demonstrates a high level of fitness.

A different trend is observed for the values generated at the $y_2$ output (Fig. 4(b)). Initially, there is a slight increase of the value and stabilization at sports level of 65–64 seconds. In the later stages of a career it can be seen that as the athlete's sports level increases, the $y_2$ value decreases.

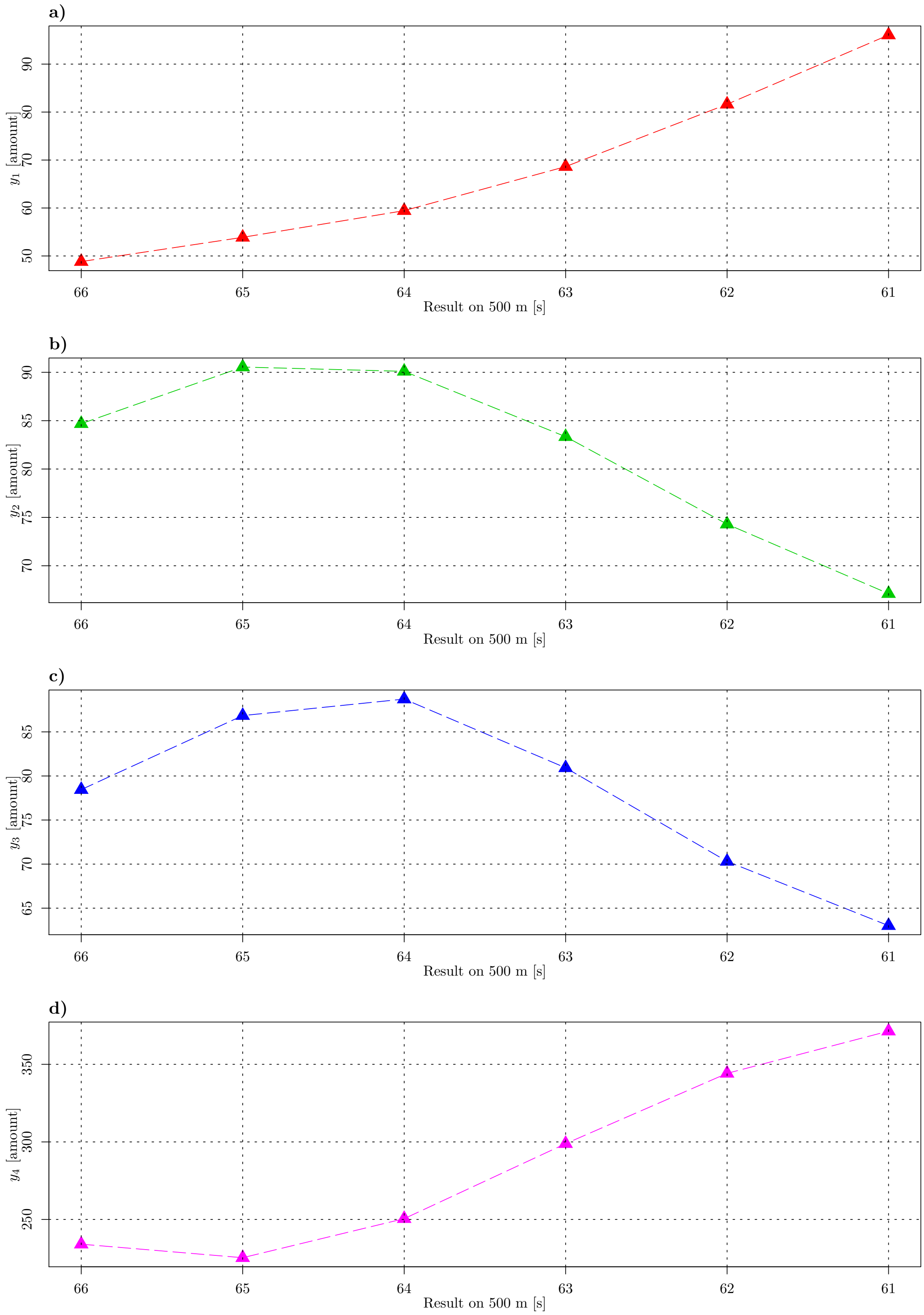


Figure 4: Training loads generated by the RBF network for a hypothetical athlete (age 21, body height 185 cm, weight 75 kg); The X-axis represents the expected results ranging from 68 s to 62 s. The Y-axis represents the value of training loads.

The third set of generated training load are runs over 8–12 hurdles ($y_3$). As can be seen from the presented graph (Fig. 4(c)) the value of these load increases until the athlete achieves a 64 s result. Subsequently, as the sports level increases so the size of this load decreases. A similar situation was observed for $y_2$.

The final set of training loads analyzed are hurdle runs in varied rhythms ($y_4$). The values of these loads change in non-linear fashion during the whole period being considered (Fig. 4(d)). In the early stages a career the value of these loads is low. It is significant that when the outcome is equal to 65 s the value of $y_4$ grows steadily, assuming its maximum value when an athlete has reached the highest level of fitness.

# 4 CONCLUSIONS

In this paper the model for generated training loads to develop techniques was calculated. The model was calculated using artificial neural networks with radial basis functions. The best RBF network has seven neuron in the hidden layer and generates errors at the level of 21%.

The generated training loads change non-linearly over the whole of an athlete's career; the training loads $y_3$ (runs over 8–12 hurdles) can serve here as an example. Their value increases systematically up to the moment when the athlete achieves an intermediate level (approx. 64 s in a 500 m flat run), and after that it decreases to the end of the athlete's career. The analysis also shows that at a high sports level the size of $y_1$ and $y_4$ should be increased (a run over 1–3 and 8–12 hurdles) and the size of $y_2$ and $y_3$ should be decreased (runs over 4–7 hurdles and hurdles runs in varied rhythm).

The implementation of artificial neural networks with radial basis functions in training loads analysis can support the hurdles training process. The results obtained can be regarded as suggestions to be used while planning these loads.

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