DETERMINATION OF TRAINING LOADS OF FFEMALE SPRINTERS WITH THE USE OF NEURAL NETWORKS

by

Igor Ryguła*

Past experience indicates that speed exercises, forming the basis of sprinting successes, should take into account the specification of goals and particularity of used training means. Specification of goals presupposes the necessity of developing such features and characteristics of motion that determine the final speed of the sprinter. Peculiarity of means should depend on keeping structural similarity of directed, special and competition specific exercises. Because of the complexity of the processes determining speed training and danger of speed stabilization, the central position is taken by effective combining of methods containing optimum proportions of standard and variable forms of speed exercises (Sozański, Walencka 1988).

This paper shows that an extremely important element of developing speed includes the proper (quantitative) structure of training loads. This means that the chosen exercises should reflect metabolic processes, which depend on the character of performed work, their intensity, duration, number of repetitions and time of rest periods. From the point of view of training effectiveness, it is extremely important to find the correct tool for choosing means in a given training cycle. The results confirm the experiences of coaches and sport scientists, that the structure of volume and intensity of training loads should be individually chosen with consideration of predispositions of separate athletes. Individualization of training is the most important condition for its optimization.

Key words: *sport training, artificial neural networks, optimal control, speeds.*

Introduction

The result in track sprint events (60 m, 100 m, 200 m and 400 m) depends on a set of closely connected predispositions and abilities. Of high significance are morphological and functional predispositions concerning structure of

* Prof., Dep. of Theory of Sports, Acad. of Phys. Educ., Katowice
Correspondence address: 72a Mikolowska Str. 40-065 Katowice, Poland

muscles, functions of the central and peripheral nervous system, efficiency of enzymatic reactions (influencing the rate energy production) and many other characteristics.

Explosive strength is the fundamental motor ability of a sprinter, enabling him to reach maximum running speed and the ability to relax muscles not directly engaged in a given phase of running. On the basis of many years of research, we obtained insight into the detailed structure of biomechanical dependencies (Grimshaw 1995, Rubin, Ilin 1978), physiological and (Winkler, Gambetta 1987), biochemical reactions (Hautier et al. 1994, Mader 1988), as well as general and specific physical efficiency, influencing the result in track sprint events (Ważny 1986). Many papers exist on the methods of speed development (Sozański, Witczak 1980) and conditions for speed improvement in so-called sports ontogenesis (Dintiman, Ward, Telez 1997), however no works exist, enabling the determination of optimal training loads in sprinting. This problem requires a urgent solution.

Published papers suggest several ways to solve this problem. First of them depends on presenting the volume and intensity of training loads in the framework of the so-called theoretic "model of the champion " (Iskra, Kosmol 1994). The second way depends on using average values of training means made in a given cycle by a group of elite athletes. Such an approach has enabled to develop standards of training work for athletes on separate stages of sport ontogenesis (Kawierin and Szustin 1981, Otrubianikow and Razumowski 1988, König 1989). Both solutions have a number of weak points. The most important seem to be : impossibility of duplication of the assumed training concept ("model of the champion") and neglecting individual predispositions of separate athletes (tables of standards). These limitations are not present in a third approach, which depends on computing the structure of training loads on the basis of a mathematical model (Ryguła 2000, Mester and Perl 2000), which is the aim of this paper.

The aim of this paper is to present a new approach to determining training loads in a group of 16 and 17-year old female sprinters, based on the neural optimization model.[1]

[1] Making optimal decisions based on a mathematical model is called optimal control.

In this way we attempt to answer the following research questions:

1. Which of the used training means have the strongest influence on the increase of results in 16 and 17-year old female sprinters?
2. Which procedures can be applied for the optimization of training loads in sprint training?

Methods

The research material for this investigation includes 20 female sprinters aged 16 and 17, practicing in athletic clubs of Silesia. The girls were subjected to a two-year investigation in accordance with the assumptions of the **experimental model. RX_n^n Y_n^n investigation** scheme was used, that is more than one dependent variable (Y_n), n dependent variables (X_n) with the use of randomization (R).

In this investigation, the role of **state variables** (independent) is played by the following variables:

1. Morphological characteristics (body height, body mass, length and circumference of thigh and shank, concave shape of foot on the basis of Clarke angle, body composition – lean body mass based on model BIA - 101/S impedance analyzer, body proportions - Roher index. The measurements were made in accordance with principles used in sports anthropology (Drozdowskai 1979).
2. Speed (starting speed, from start to 5m, maximum speed, flying 20m sprint). The measurements were made with a computer system (Ryguła 1996).
3. Dynamic strength (mechanical power) of lower limbs - based on a computer system (Ryguła 1997).
4. Anaerobic efficiency (Wingate test) - based on a computer system (Ryguła 1997).
5. Aerobic efficiency (PWC_{170} test) - based on a computer system (Ryguła 1997).
6. Anaerobic threshold (AT). Lactate evaluation was performed by a photometric method, dr Lange Company, AT - with Ch.T. Chille computer program (Ryguła 1997).

In total, 12 state variables were measured. All measurements were made in home clubs of respective athletes, according to methods described in papers (Ryguła 1996, 1997).

The role of controls was played by training means chosen, systematized and described by Perkowski in a publication edited by Sozański and Śledziewski (1995). Controls (training means) were changed every two months. **The quality index** included the 100 m result.

In accordance with earlier papers (Ryguła, Wyderka 1993, Ryguła 2000), as an initial model of sport training, a set of differential equations has been assumed in the form:

$$\frac{dx_i}{dt} = F_i(t,x_1,...,x_r,u_1,...,u_s) \qquad i=1,...,r$$

where:

x_i is the i-th state variable, i=1,...,r,

u_j is the utilization of the j-th training means, j=1,...,s.,

$u_j \in [0,1]$, 0 - absence, 1 - maximum possible utilization of the j-th training means.

The form of F_i function is following:

$$F_i(t,x_1,...,x_r,u_1,...,u_s)=$$

$$= \sum_{j=1}^{r} a_{ij}x_j + \sum_{j=1}^{r}\sum_{k=1}^{s} b^i_{jk}x_ju_k + \sum_{j=1}^{s} c_{ij}u_j + d_i + h_i(t,U) \quad i=1,...,r \qquad (1)$$

Our **optimization problem** has the form: Determine time functions of control variables $U(t)=(u_1(t),...,u_s(t))^T$,$u_i(t)\in[0,1]$ i=1,...s, $t\in[0,T]$ in such way, to obtain maximization of $x_1(T)$, where $X(t)=(x_1(t),...,x_r(t))^T$ is a solution of (1) for initial condition $X(0)=X_0$. X_0 is the initial state of the athlete, for whom we are determining optimal training.

Because of fact, that the form of F function is nonlinear, in this work, in addition to improvement of using a model developed earlier, an attempt was made to use other methods of building F function. Specifically, a method of using artificial neural networks (ANN) has been proposed, which may provide an algorithm of computing the value of F function, not just its analytic form. The benefit of this approach is a possibility of modeling strongly nonlinear functions and obtaining great degree of their generality (Ryguła 2000a).

Principles of operation of artificial neural networks

Neural networks are characterized by simple mathematical apparatus, their use is easy and learning algorithms are transparent. In this work a specific neural network was used - nonlinear feedforward network, learning with the use of back propagation algorithm (Lula 1999).

The action of single neuron consists of two steps. In the first step, the neuron receives a sequence of numbers $x_1 \dots x_m$, called input pulses and computes the sum:

$$e = \sum_{i=1}^{m} w_i x_i + w_o$$

and then the value of function

$$Y = \varphi(e)$$

where φ is called activation function and corresponds to threshold potential. Live neuron emits its signal only when sufficiently excited.

$w_0 \dots w_m$ coefficients, called synaptic weights and φ function constitute full characterization of neuron. During the learning process of the neuron the weights values are corrected.

Because of the simplicity of correction formulas for the weights, most frequently used form of φ is:

$$\varphi(x) = \frac{1}{1 + \exp(-\beta x)}$$

The scheme of a neuron is shown in Fig. 1.

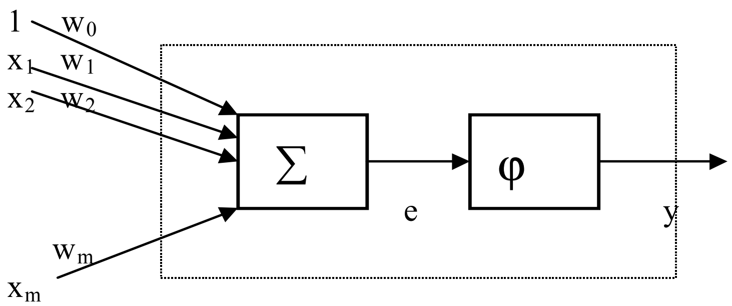

Fig. 1. Scheme of operation on a neural model

The neural layer is a group of n neurons with the following properties:

a) Each of neurons receives the same sequence of input pulses $x_1 \ldots x_m$,

b) Together, the layer produces n numbers $y_1 \ldots y_n$, denoted with Y.

The (m, n) pair is called the layer dimension.

Mathematically, the neural layer is therefore a nonlinear function Φ_w of the $R^m \rightarrow R^n$ type. The neural network is a sequence of layers $W_1 \ldots W_k$ such that $Y_0 = X$ $Y_i = \Phi_{W_i}(Y_{i-1})$ i=1,..., l

Vector $X \in R^m$ is called network input, Y_l - the network response to this input.

The dimensions of layers should be chosen to enable assembling Φ_w function. The value of input and the response will depend on the use of network.

The number of input pulses will be denoted m and input vector with symbol $X=(x_1 \ldots x_m)$. The dimension of network response, that is number of neurons in last layer will be denoted n and the response itself with symbol Y=(y1 ... yn).

The schematic of neural model of dynamic object is shown in Fig. 2.

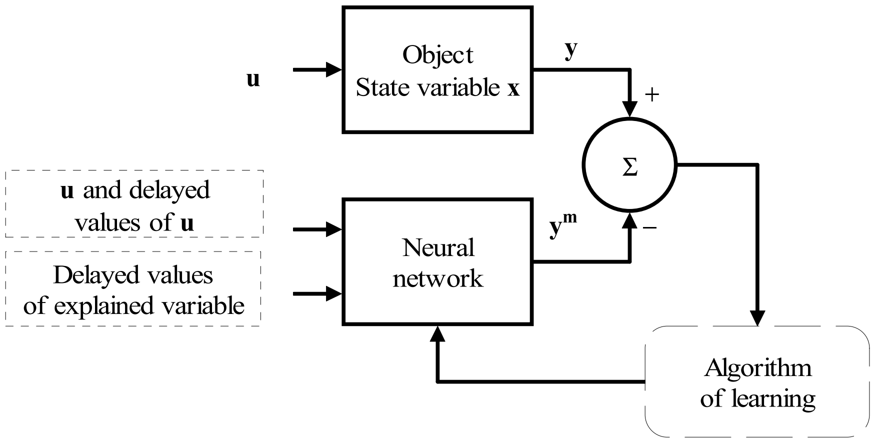

Fig. 2. Scheme of a neural optimization model

Such defined neural network may be used to determine the relation:

(state variables, control) → increment of state variable,

that is, F function in Equation (1).

In order to obtain proper values of synaptic weights, the network should be subjected to teaching process. Network teaching process will be supervised teaching. This means that so-called teaching sequence is determined in the form:

$$(X_1,Z_1) \ldots\ldots\ldots\ldots (X_M,Z_M)$$

where X_i is an input vector of the network and Z_i - correct response of the network for this input. The difference $Z_i – X_i$ will be an error of the response for given configuration of all neurons in the network. Learning of a single neuron in the network will depend on correcting its weights using input pulses, output value and error value.

New values of the weights are determined on the basis of equation (Osowski 1996):

$$W_i^{(j+1)} = W_i^{(j)} + \eta_1 \delta^{(j)} y^{(j)} (1-y^{(j)}) x_i + \eta_2 (W_i^{(j)} - W_i^{(j-1)}) \qquad i = 0, \ldots, m$$

where: i - number of input component,

j - iteration number,

η_1, η_2 - learning parameters,

$\delta^{(j)}$ - error in the j-th iteration,

$y^{(j)}$ - output value in the j-th iteration.

The last element of the sum is called momentum components as it provides a degree of inertia to introduction of changes during network teaching.

While for the neurons of the output layer, the error is computed directly on the basis of standard, for the hidden layer and input layer a method of backward projection

$$\delta_p^{(j)} = \sum_k W_p^{(k)(j)} \delta_k^{(j)}$$

where: p - is neuron parameter in hidden layer,

j - neuron number in output layer,

$\delta_k^{(j)}$ - error of neuron with number k in output layer.

Errors computed in this way are used in correction formula for weight.

Construction of artificial neural networks

In the first stage, for the construction of the model, we have chosen *r* state variables and *s* control variables and *z* athletes, for whom these parameters were measured or determined in the period $[t_1, t_2]$. Next, we transform time interval into $[0, T]$, where $T=t_2–t_1$. Let τ denote basic time unit and $T=N\tau$. We assume that each athlete has all measurements in each time unit. Let's denote measurements as follows:

$\xi_i^l(t)$ - value of the i-th state variable for the l-th athlete in the t-th time unit,

$\tilde{\theta}_j^l(t)$ - value of the j-th state variable for the l-th athlete in the t-th time unit,

i=1,...,n, j=1,...,m, l=1,...,z, t=0,...N. Using this data we will build and teach neural network, being algorithm of computing the value of F function. Because this network has to represent function of $R^{r+s} \to R^r$ type, we have input dimension m=r+s and input layer dimension n=r. Other parameters of the network would have to be chosen empirically.

For the needs of the algorithm we have to transform all data into [0, 1] range. This was done in the following way:

for each variable we determine its range $[\delta_j, \gamma_j]$ j=1,...,r+s,

we make transformation $\xi_j^l = \dfrac{\xi_j^l - \delta_j}{\gamma_j - \delta_j}$ j=1..r

and $\theta_j^l = \dfrac{\tilde{\theta}_j^l - \delta_{j+r}}{\gamma_{j+r} - \delta_{j+r}}$ j=1,...s, l=1,...,z.

The teaching sequence for the network under consideration has the form:

Input – $(\xi_1^l(t),...,\xi_r^l(t),\theta_1^l(t),...,\theta_s^l(t))$ l=1,..,z , t=0,...,N-1

Output - $(\xi_1^l(t+1)-\xi_1^l(t),...,\xi_r^l(t+1)-\xi_r^l(t))$ l=1,..,z , t=0,...,N-1

The length of the teaching sequence is M=N*z.

Quality of fitting the network to data may be expressed with index

$$H = \sum_{i=1}^{r} \sum_{l=1}^{z} \sum_{t=0}^{N-1} ((\xi_i^l(t+1) - \xi_i^l(t)) - y_i^l(t))^2 \qquad (2)$$

where $y_i^l(t)$ is network response to the input –

$(\xi_1^l(t),...,\xi_r^l(t),\theta_1^l(t),...,\theta_s^l(t))$ i=1,...r, l=1,..,z , t=0,...,N-1

In practice, the greatest computational difficulty is determination of the maximum of Hamilton function. The main reason lies in interdependency of training means, for instance the sum of training means is limited with duration of training, some means are mutually exclusive in one training session.

For this reason, to make the control as real as possible, the team of experts should determine certain set of possible training standards and seek among them for the best one at given stage of computations.

In the investigation, a measure of total load was the total duration of training means used in defined range of intensity. Each training cycle may be analyzed through detailed load parameters, expressed in units of time and forming specified structure of loads.

Time of using separate training means in all intensity ranges formed decision variables.

The collected material was initially processed with the use of basic methods of descriptive statistics. On this basis the variability was determined and fitting of results to standard distribution. The following statistic measures were analyzed: arithmetic mean ($\bar{x}$), standard deviation (S), variability index (V), asymmetry index (A_s) and kurtosis index (Ku). Statistical characterization of scores of investigated athletes before the beginning of the experiment is shown in Table 2.

Results

To simplify the analysis, after the initial statistical analyses it has been decided to use three state variables (with statistical characteristics shown in Table 2) and all controls used in training (Table 3) as a basis for construction of the model.

Table 2. Statistical characteristics of scores of investigated athletes before the beginning of the experiment.

State variables	$\bar{x}$	S	A_s	Ku	V
100 m run [s]	13.09	0.60	–0.50	0.08	4.58
30 m run [s]	4.19	0.23	–1.60	2.19	5.48
Standing long jump [m]	2.37	0.18	1.07	2.56	7.59

Chosen parameters of descriptive statistics of the state variable of the investigated group before the beginning of the experiment are shown in Table 2.

The values of asymmetry and kurtosis indexes indicate that distributions of measurement data do not differ from Gauss-Laplace distribution. On their basis we may say that all analyzed characteristics have a moderately asymmetric distribution, differing little from a normal distribution. Therefore we may assume that subjects taking part in the model experiment well represent the population of female sprinters.

14 training means used were assumed as control variables.

Table 3. Kinds of training means and their designations (Sozański, Śledziewski 1995)

Kind of training means	Unit	Information area (V-D-S)	Energy area (ranges: 1-6)
U1	min	versatile	First
U2	min	versatile	Second
U3	min	versatile	Third
U4	min	versatile	Fourth
U5	min	versatile	Fifth
U6	min	versatile	Sixth
U7	min	directed	Third
U8	min	directed	Fourth
U9	min	directed	Fifth
U10	min	directed	Sixth
U11	min	special	First
U12	min	special	Second
U13	min	special	Third
U14	min	special	Fourth

According to the procedure described in this paper (Ryguła 2000a), the values of coefficients of equation (1) were determined and they are presented in Tables 4 - 9.

Table 4. Values of coefficients a_{ij} (i,j=1,...,3) in Equation (1).

Equation for variable	State variable		
	X1	X2	X3
X1	-10.30	-15.25	21.55
X2	4.99	8.40	53,24
X3	4.86	23.47	-28.95

Table 4 shows the influence of state variables x1-x3 on the changes of these characteristics. It may easily be seen that the change of variables x1 and x2 is mostly influenced by dynamic strength, evaluated with standing long jump (x3). The improvement of standing long jump depends mainly on variable x2.

Table 5. Value of coefficients b^1_{jk} (j=1,...,3;k=1,..,14) in equation for variable X_1.

Control variable	State variable		
	X1	X2	X3
U1	209.87	1228.97	-81.96
U2	76.77	1710.08	181.38
U3	0.15	11.45	-13.24
U4	-9.9	69.9	2.5
U5	19.81	-17.17	-55.4
U6	-22.59	-48.31	28
U7	-7.71	-55.95	-5.39
U8	126.49	1337.34	318.72
U9	3.18	30.97	0.42
U10	-3.26	-45.49	4.17
U11	-14.77	-42.21	27.65
U12	-0.42	3.37	2.6
U13	-0.28	-4.68	-14.17
U14	5.76	51.28	-0.88

Table 6. Value of coefficients b^2_{jk} (j=1,...,3;k=1,..,14) in equation for variable X_2

Control variable	State variable		
	X1	X2	X3
U1	-86.72	-489.55	16.62
U2	29.67	-401.86	-134.18
U3	-0.15	-5.84	2.95
U4	4.2	-16.4	2.13
U5	-9.79	-0.22	20.23
U6	15.3	51.79	-9.96
U7	0.89	13.09	5.49
U8	-35.18	-481.28	-167.95
U9	-1.98	-17.92	0.31
U10	0.97	17.76	0.55
U11	5.07	22.36	-4.5
U12	0.09	-0.81	-0.68
U13	-1.39	-8.25	4.35
U14	-4.76	-32.31	9.45

Table 7. Value of coefficients b^3_{jk} (j=1,...,3;k=1,..,14) in equation for variable X_3.

Control variable	State variable		
	X1	X2	X3
U1	-11.37	6.44	132.32
U2	-9.33	48.39	-25.38
U3	-1.59	-8.46	1.23
U4	5.42	49.42	-6.21
U5	-13.5	-128.32	-22.82
U6	7.56	107.44	34.9
U7	-1.02	-7.26	0.73
U8	40.94	419.31	109.64
U9	0.67	7.05	-1.25
U10	-0.28	-11.34	0.91
U11	-4.67	-27.03	5.38
U12	0.81	4.14	-0.6
U13	0.41	3.4	-0.68
U14	4.08	18.78	-2.25

Table 8. Value of coefficients c_{ij} (i=1,...,3;j=1,..,14).

Control variable	Equation for variable		
	X1	X2	X3
U1	-66.63	-27.75	-6.04
U2	-96.9	-24.77	-0.19
U3	0.02	0.17	0.43
U4	-3.57	0.68	-2.49
U5	3.08	-0.73	8.41
U6	1.81	-2.67	-7.63
U7	33.44	-0.97	0.37
U8	88.88	34.22	-28.5
U9	-1.75	98,22	32,44
U10	2.24	-0.98	53,89
U11	1.62	-1.21	1.36
U12	-0.26	0.06	-0.22
U13	0.93	0.28	-0.17
U14	-2.86	1.4	-1.05

Table 9. Value of coefficients d_i (i=1,...,7) .

Equation for variable	Value
X1	0.000
X2	0.000
X3	0.000

According to Equation (2) coefficients of model fitting to empirical data were computed. They constitute multidimensional equivalent of relative error (ratio of difference between accurate and approximate value and accurate value multiplied by 100). The results are shown in Table 10 below.

Table 10. Coefficients of fitting for separate equations.

Equation for variable	δ_i [%]
X1	3.8
X2	3.7
X3	3.4

The values of coefficients of fitting are very small, which indicates good accuracy of the model. It was therefore assumed that model sufficiently approximates experimental data.

Verification of the model

After determining the model, it was used to compute the values of state variables at the end of training period for each of the athletes. As a control in the model the real training was assumed. Table 11 shows percentage differences (relative error) between observed results and results computed with a model.

Table 11. Comparison of real results with results obtained from the model

Athlete no.	100 m result	30 m result	Long jump
1	*-6.3*	*-11.2*	*4.5*
2	0.8	2.3	-2.7
3	3.1	3.2	-9.0
4	**-0.5**	**1.9**	**0.0**
5	**-0.1**	**-0.5**	**0.4**
6	3.7	6.3	-1.7
7	*-6.3*	*-7.3*	*2.4*
8	-4.9	-4.1	2.9
9	**0.3**	**0.7**	**0.8**
10	2.4	2.4	0.4
11	**0.1**	**0.2**	**3.0**
12	*4.8*	*7.0*	*-11.3*
13	-0.4	-1.4	6.0
14	**1.7**	**0.5**	**0.4**
15	-2.5	-2.1	2.2
16	3.9	4.8	-2.9
17	2.6	1.8	-4.7
18	-2.0	-3.1	3.0
19	*0.1*	*-4.2*	*-13.6*
20	-3.8	-6.0	3.5

As can be seen, the model produces scores very near the observed results. However, there are athletes (marked with italics), for whom the model gives less accurate results. In further investigations they should be removed and a new model should be built in a attempt to find other factors that may cause these differences. The best fit has been shown in bold print.

Comparison of various training approaches

At first as a quality index the 100 m result was assumed and it was minimized. Table 12 shows percentage improvement of result related to the end of the training period.

Table 12. Comparison of optimum results for all athletes

No.	100 m result	Percentage improvement
1	12.55	4.3
2	13.55	14.7
3	13.6	15.4
4	13.3	10.6
5	13.48	11.1
6	13.42	11.9
7	12.32	6.6
8	12.49	7.8
9	12.85	3.3
10	12.95	11.2
11	13.7	15.9
12	13.8	14.9
13	13.55	13.0
14	13.38	13.8
15	13.08	9.6
16	13.32	8.5
17	12.65	8.8
18	12.3	6.3
19	11.36	0.1
20	12.25	6.0

Next, a sprinter was chosen with results best fitting the model (no. 5) and optimal controls were determined for her, assuming as quality indexes the 100 m result, then 30 m result and the standing long jump result.

Table 13. Optimal scores for one athlete and each state variable

Event	Real score	Computed scores		
		I	II	III
100 m	13.48	11.98	12.65	13.87
30 m	4.25	4.20	3.92	4.26
Long jump	2.45	3.38	2.75	3.39

I - 100 m result as quality index
II - 30 m result as quality index
III - standing long jump as quality index

An example of W1 optimal controls at different quality indexes for chosen athlete is shown in Fig, 3.

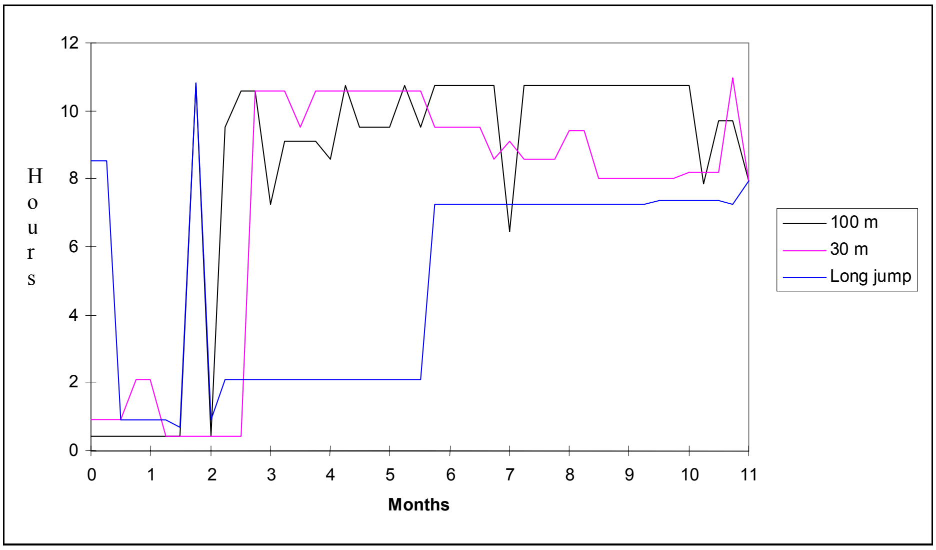

Fig. 3. Variants of optimal controls

Training intensity for obtaining best results in the 100 m run and 30 m run is very similar. For best results in the long jump it is markedly different.

Discussion

The author decided to use three state variables and fourteen controls for construction of the model. The smaller number of state variables was chosen for procedural reasons, as the use of neural models requires a relatively great number of observations and small number of parameters.

The paper considers the influence of all factors that significantly influence analyzed quality indexes. Constructed model enables analyzing the influence of increase of each state variable on chosen state variable which will be treated as a quality index. Table 4 indicates that the greatest influence on the improvement of 100 m results had variable x_3, while the improvement of standing long jump results depended mainly on variable x_2 (30 m). The improvement of 30 m sprint times was mainly influenced by improvement of dynamic strength (x_3). These results prove that speed abilities, which are demonstrated by performing short exercises with maximum intensity are dependent on the possibility of overcoming external resistance and therefore influence the result of female sprinters.

For analyzing of the influence of separate factors on the improvement of chosen quality index, the products of state variables and control variables, presented in Tables 5 - 7 may be of interest. The analysis may use absolute values of these equation coefficients as well as their sign, because this enables analyzing their influence on the improvement of given quality index.

Of special interest are increments of state variables depending on control variables, presented in Table 8. They indicate that the improvement of 100 m results of 16 and 17 year old female sprinters was positively influenced above all by controls U8 and U7 (means with directed character, coming from the area of anaerobic - lactic acid processes and mixed aerobic-anaerobic processes). The strongest negative influence on the improvement of 100 m results of these athletes had U2 and U1 controls. It is understandable that for athletes at this stage of training such means should have just auxiliary, not dominating character.

Slightly different is the problem of the influence of training means used on the improvement of 30 m results. The greatest positive influence at this stage of sport ontogenesis have means with symbols U9 and U8 and greatest negative influence have controls U1 and U2. It seems evident that for improvement of maximum speed of these athletes short-term means of greater intensity should be mainly used, with minimum use of versatile means from the area of aerobic and maintaining processes.

The results presented in Table 8 indicate that to improve the standing long jump results, we should use in the right proportion, means engaging anabolic processes and coming from anaerobic, non lactic acid processes. Very interesting is the fact that at this stage of sports development, the improvement of all state variables (X1 - X3) was very slightly influenced by means with character of special action. It may mean that means of directed action are not yet exhausted, and means of special character will find proper use in further stages of athletic development.

The results of our investigation are in agreement with results of other authors who have shown that most important element of speed development is variability of training means, enabling stimulation of adaptive changes and avoiding stagnation of the development of this motor capability (Dintiman, Ward, Telez 1997).

Observations made in this work confirm suggestions of numerous scientists (Bompa 1999, Sozański and Zaprożanow 1995) that effectiveness of sports training of females in sprint track events is conditioned by using training means specific for this group, that develop motor functions and abilities (above all running speed, explosive strength, speed endurance and coordination) while stimulating desirable adaptive changes (mostly in the area of anaerobic efficiency) (Raczek 1989, Sozański 1986).

In view of the obtained results, the question of using optimal control model should be answered. This paper presents two of them:

- Evaluation of the influence of different factors on the results;
- Evaluation of the influence of specified training cycles for a given athlete.

The results shown in Table 13 and Fig. 3 enable to conclude that optimization implies individualization of training (Filin 1986, Kozioł 1985, Brejzer 1991). For each individual there is a defined volume and intensity of training, conditioning constant improvement of results (Ryguła, Wyderka 1993, Arakelian, Mirzojew 1997).

The results of this investigation allow for the following **conclusions**:

1. For each individual, independently of the stage of sports development, a group of training means may be chosen that positively and negatively influence the improvement of chosen quality index.
2. In a group of 16 and 17 year old female sprinters, positive influence on the improvement of 100 m results had mainly means of directed character, engaging anaerobic - lactic acid processes.
3. The improvement of 30 m results of these athletes was mainly brought by exercises of anaerobic character, non lactic acid processes, from the area of directed means.
4. The development of dynamic strength, evaluated by the standing long jump, was positively stimulated by means with directed character, which generated anabolic changes.

REFERENCES

Arakelian J., Mirzojew O. 1997. Modeli sprinterow i barieristow. Legkaja Atletika 2, 10.

Bompa T.1990.Theory of training planning. RCMSzKF i S, Warszawa.

Brejzer W.W., Iwkin G.W., Maljutow M.B. 1988. Programmirowanie treninrowocznoj nagruzki w godicznom cikle podgotowki. Teoria i Praktika Fiziczeskoj Kultury 3, 36-38.

Dintiman G, Ward B., Telez T. 1997.Sports Speed. HKP Champaign.

Drozdowski Z. 1979. Sport anthropology. AWF, Poznań.

Filin V.P. 1986.Vospitanie fiziceskich kacestv u junych sportsmenov. F i S, Moskwa.

Grimshaw P. N. 1995. A kinematic analysis of sprint hurdles training strategies (isolation drills). Athletics Coach 4, 12-15.

Hautier C. A., Wauassi D., Arsac L. M., Bitanga E., Thiriet P., Lacour J. R. 1994. Relationships between post competition blood lactate concentration and avarage running velocity over 100 m and 200 m races. European Journal ofApplied Physiology 68, 508-513.

Iskra J., Kosmol A. 1994. Analysis of many years training cycle of a runner (400 m hurdles). Sport Wyczynowy 11, 32-43.

Kawierin W., Szustin B. 1981. Modelnyje charakteristiki w bariernom biegie. Legkaja Atletika 5, 9-10.

Kozioł R. 1985. Mathematical formalization of sport problems. Zeszyty Naukowe AWF Poznań nr 41.

König E. 1989. Zum gegenwärtigen Entwicklungsstand und zu Fragen der Künftigen Entkwicklung im 400-m-Hürdenlauf der Frauen. Leichtathletik 17, 529-532.

Lula P. 1999. Unidirectional neural networks in modeling economic phenomena. A.E. Kraków.

Mader A. 1988. Transcription-Translation activation feedback circuit as a function of protein degradation, with the quality of protein mass adaptation related to the average functional load. Jour Theo Biol 134, 2 – 17.

Mester J., Perl J.1999. Unconventional simulation and empirical evaluation of biological response to complex high training loads. In: Parisi P., Pigozzi F., Prinzi G. (Eds.): Sport Science ´99 in Europe. Rome, 163.

Nowikow A.A. i in. 1976. O razrabotkie modielnych charaktieristik sportsmienow. Tieorija i Praktika Fiziczeskoj Kultury nr 6.

Osowski S. 1996. Neural networks in algorithmic approach. WNT, Warszawa.

Otrubiannikow P. J., Razumowski J. A. 1988. Sprint s barierami. Zdorowia, Kijów.

Perl J. 1997. Aspekte unkonventioneller Modellbildung – exemplarische Anwendungsmöglichkeiten in der Sportwissenschaft. Zur Veröffentlichung angenommen bei: Sportwissenschaft 7.

Raczek J. 1989. Training young people in competition sport system. AWF Katowice.

Rubin W.S., Ilin N.S. 1978. Osnowanyje faktory charakterizujszczije specjalnuju skorostno-siłowuje i techniczeskuju podgotowliennost barieristow. Teoria i Praktika Fiziczeskoj Kultury 11, 16-18.

Ryguła I. 2000. How to construct mathematical model of sport training. Journal of Human Kinetics vol. 3.

Ryguła I., Wyderka Z. 1993. Elements of control and optimization in sport training. AWF Katowice.

Ryguła I. 2000a. Artificial neural network as a tool of the sport prediction. Journal of Human Kinetics vol. 4.

Ryguła I.1996. Computer tests for evaluation of preparation of football players. AWF Katowice.

Ryguła I. 1997. Methods of diagnostics of young people with sport aptidude. ZMSzZSKF"Makroregion Śląski".

Sozański H. 1986. Theoretic principles and some practical solutions in sports of children and young people. PTNKF, Warszawa.

Sozański H., Śledziewski D. 1995. Training loads. RCMSzKFiS Warszawa.

Sozański H., Walencka B. 1988. Basic principles of speed development. Sport Wyczynowy, nr 2-3.

Sozański H., Witczak T. 1980. Speed training. Sport i Turystyka, Warszawa.

Sozański H., Zaporożanow W. 1993. Guidance as training optimization factor. RCMSKFiS, Warszawa.

Ważny Z. 1986. Process of sport training - an outline. WFS, Katowice.
Winckler G., Gambetta V. 1987. Classifications of energy systems in sprint training. Track Technique 100, 3193-3195.