A NONLINEAR APPROACH TO THE ANALYSIS AND MODELING OF TRAINING AND ADAPTATION IN SWIMMING

Andreas Hohmann, Juergen Edelmann-Nusser[1], and Bernd Henneberg[2]
University of Potsdam, Potsdam, Germany
[1]Otto-von-Guericke-University, Magdeburg, Germany
[2]Olympic Training Center Halle/Magdeburg, Magdeburg, Germany

The purpose of the study was to demonstrate that the adaptative behavior of an elite female swimmer (Olympic silver medalist in the 400 m freestyle) can be modeled by means of the nonlinear mathematical method of a neural backpropagation network. Therefore, the training process of 107 successive weeks was carefully controlled and documented. For the data analysis a multilayer perceptron network was trained with the performance output data of 28 competitions within that time period and the training input data of the last four weeks prior to the respective competitions. After the iterative training procedure the neural network is able to model the resulting competitive performances on the basis of the training data from the two-week-taper phase and also from the earlier two-week-overload phase preceeding the respective competitions with high precision.

KEY WORDS: swimming, training analysis, competition performance, adaptation, single-case study, longitudinal design, time-series analysis, neural network, multilayer perceptron

INTRODUCTION: The thorough analysis of periodized training processes is one of the most important issues of training science with regard to two crucial elements: a) the understanding of the time course of adaptation (Rowbottom, Keast, & Morton, 1998), and b) the optimum monitoring of training. In contrast to linear mathematical concepts that have commonly been used for training analysis (Calvert, Banister, Savage, & Bach, 1976; Banister, & Calvert, 1980; Banister, 1982; Busso, Häkkinen, Pekarinen, Carasso, Lacour, Komi, & Kauhanen, 1991; Hohmann, 1992; Busso, Denis, Bonnefroy, Geyssant, & Lacour, 1997; Mujika, Busso, Geyssant, Chatard, Lacoste, & Barale, 1986; Fitz-Clarke, Morton, & Banister, 1991; Mujika, Busso, Lacoste, Barale, Geyssant, & Chatard, 1996; Hooper, & Mackinnon, 1998; Chatard, & Mujika, 1999), this current study was based on a synergetic concept of training and therefore the nonlinear method of a neural backpropagation network was used to model a training process.

The use of the linear mathematical concept in training analysis has first roots in the idea that the ’system athlete’ can be precisely monitored like a ‘trivial machine’ (von Foerster, 1988). In that kind of cybernetic thinking, the system athlete functions in a way like a technical closed circuit, where a definite amount of training input leads to an equivalent raise in the performance output. On the basis of the cybernetic approach several studies focussed on the adaptation of swimmers to certain training regimens. In these studies the investigators used linear methods like differential equations or regression analysis to model the adaptative behavior as the result of different training parameters.

Calvert, Banister, Savage, & Bach (1976) introduced an antagonistic fitness-fatigue-model to study the input-output relationship between the quantity of training and time of a criterion performance in a single-case study on a swimmer. The authors calculated arbitrary training units assigned to three categories of the intensity of the training input: warm-up intensity (I), low quality intensity (II) and high quality intensity (III). The performance output in 100 m time trials was modeled by two differential equations. The authors created a first transfer function to describe the decay of fitness as a negative training response starting immediately after the training impulse of a training session. The second transfer function described the antagonistic mechanism of the decay of fatigue, a positive result of the growing regeneration, that also starts immediately after the input of a training impulse. Finally, the investigators showed the model performance matched by linear regression analysis to actual performance of the swimmer. After the modeling had been improved by a replication of the study two years later for a training season of the same athlete, and by testing different time constants as model parameters, the authors could present a quite impressive figure that shows the results of the model fit. Unfortunately, the authors did not comment on the error of the model prediction.

Mujika and coworkers (1996) also applied the antagonistic fitness-fatigue-model of Banister (1982) to the analysis and modeling of swim training effects. By means of a multiple regression analysis on the basis of the weighted training volumes from five categories of training data (I: speed inferior to 2mMol/l blood lactate; II: close to 4 mMol/l; III: close to 6 mMol/l; IV: high lactic swimming (10mMol/l); V: sprint swimming) they could predict the actual competitive performances during a competitive season with an accuracy that ranged from 45 to 85 percent within the 18 single national top ranking swimmers.

Hooper, & Mackinnon (1999) investigated the optimal duration of taper in swimmers and found an optimal prediction in the performance improvement of 18 age group swimmers of 71 percent. As predictors the authors used the percent change after one week of taper (that is from pre-taper to after one of two weeks of reduced training before the State Titles) with the following variables: the dimensions depression, anger, confusion and vigour of the questionnaire Profile Of Mood States (POMS), the swimming force in tethered swimming, and the reported log book fatigue and muscle soreness.

The predictions that Hohmann (1992) calculated from the training input data of a water polo national team during the preparation for the Olympic Games 1988 by means of a multiple and time lagged Regression Analysis of Time Series (RATS) were comparably lower. The author included the predictors training volume of the last fifteen days prior to competition. The volume of swim training in the time course of the preceeding fifteen days showed a common variance with the observed Game Performance Index (GPI) that ranged from 5.8 to 54.8 percent for the 10 investigated players. The volume of game training could only explain 25.0 to 28.1 percent of the variance in the GPI.

From a synergetic point of view it is not very surprising that the reported predictions of competitive performances were not very good, because they are based on the linear mathematical concept (see (a) in figure 1), which seems to be inappropriate to model the black box of athletic adaptative behavior.

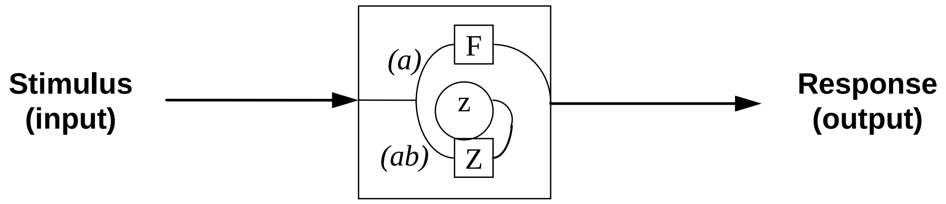

Figure 1 - The (a) Linear and (ab) Nonlinear concepts of training adaptation.

[*(a)*: As a linear model, it has to fulfil the following constraints: signal X1(t) at the input leads to y1(t) at the output; signal X2(t) at the input leads to y2(t) at the output; signal X(t)=X1(t)+X2(t) at the input leads to y(t)=y1(t)+y2(t) at the output.]

There is much evidence for the idea that the individual effects resulting from the training process are to a certain extend self-organized. The most convincing argument is that the state of performance of the system ‘athlete’ does not only change through the influence of training input, but also by other environmental influences as well as through endogenious influences (O`Toole, 1998; Rowbottom, Keast, & Morton, 1998). If the state of performance of the athlete changes by itself and in a self-organized way, then his adaptability, in the sense of his capability to absorb and respond to training, also changes over the time. As a consequence of this specific aspect of training adaptation, the same training stimulus at a later moment in time leads to quite different adaptative responses in the same athlete (Fitz-Clarke, Morton, & Banister, 1991). Therefore, the training process and the resulting adaptation in the athlete can be better understood as a complex dynamic system and described more adequately by a single case study. The training input data and performance output data have to be interpreted as two interacting time series and to be analyzed on the basis of nonlinear mathematical concepts.

METHODS: The training process lasted a total 107 weeks from week 01/1996 to week 03/1998. According to the system of Fry, Morton, & Keast (1991) it was devided into 8 preparation macrocycles including the final competitions. The 8 macrocycles consisted of 6-14 weeks (microcycles) of training preparation and 1-3 weeks of competitions.

Data Collection. The data consisted of the competitive performances and the documented training loads in three zones of swim training intensity and two categories of dryland training. The three zones of training intensity were controlled by frequent lactate testing in the course of the training process. The documented categories of training were: compensation training below the aerobic threshold (Compensation: <2 mmol/l blood lactate); maintenance aerobic endurance training slightly above the aerobic threshold (End_I: 2-3 mmol/l blood lactate); developmental and overload aerobic endurance training at and slightly above the anaerobic threshold (End_II: 4-6 mmol/l blood lactate); anaerobic power training, speed training and competitions (End_III: 6-20 mmol/l blood lactate); dryland strength training (Strength); dryland general conditioning training (General Conditioning). The competitive performances in the 400 m freestyle events were transformed according to the pointage system of the 'Ligue Europèene de Natation' into LEN-points. Therefore, we used the LEN-point table 1997-2000, that reaches from 1 to 1200 points, and where the actual World Record (e.g. in the female 400 m freestyle 4:03,85 min) serves as reference value for 1000 points.

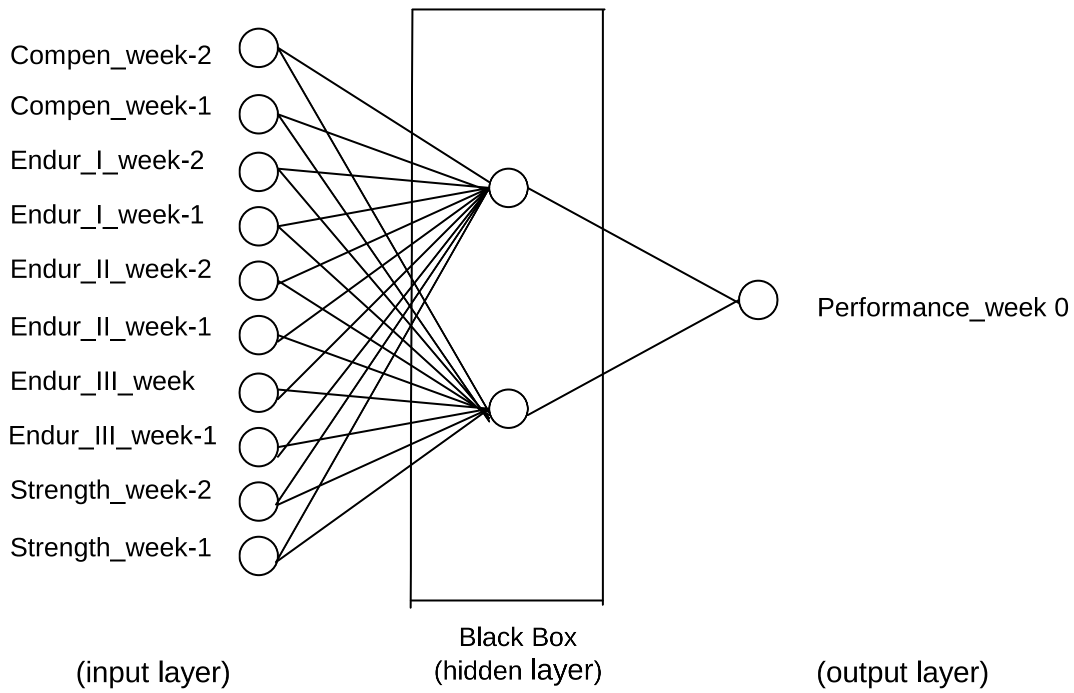

Figure 2 - The structure of the multilayer backpropagation net ('multilayer perceptron', DataEngine Inc., Aachen, Germany) used to model the interrelation between the training input data and the performance output data.

Data Analysis. In the present study a 'neural backpropagation network' (MULTILAYER PERCEPTRON, DataEngine Inc., Aachen, Germany) with three layers was used. Two analysis were conducted: one to determine the influence of the two week taper phase prior to the 28 competitions. The taper has the function to allow the athlete to recover from the high training loads before and to peak his performance. The second analysis should determine the influence of the overload training phase, that includes the weeks four and three prior to the single 28 competitions. This 'crash' phase normally contains very intense and exhaustive

training, and has the function to create a state of slight overreaching (Kreider, Fry, & O`Toole, 1998) in the athlete. That state of transient fatigue allows the athlete to reach an accumulated and thus optimal supercompensation after the later taper.
For both analysis a neural network with 10 input neurons was created (figure 2). Each neuron represented the weekly training volumes in one of the five zones of training intensity in one of the two weeks of the investigated training phase. Two hidden neurons served to represent the black box of the system 'athlete' and one output neuron to represent the competitive performance. In the first step, the multilayer network was trained with the training input data and the performance output data of 25 training and competition phases (three less than at hand) to learn the interrelation between the training input and the performance output. The training phase aimed at the weighting of all 13 neurons on the three layers and consisted of 5,000 iterative calculations of the neuron weights. Figure 3 shows the iterative training process up to the step 4732, where the mean training error was smallest.

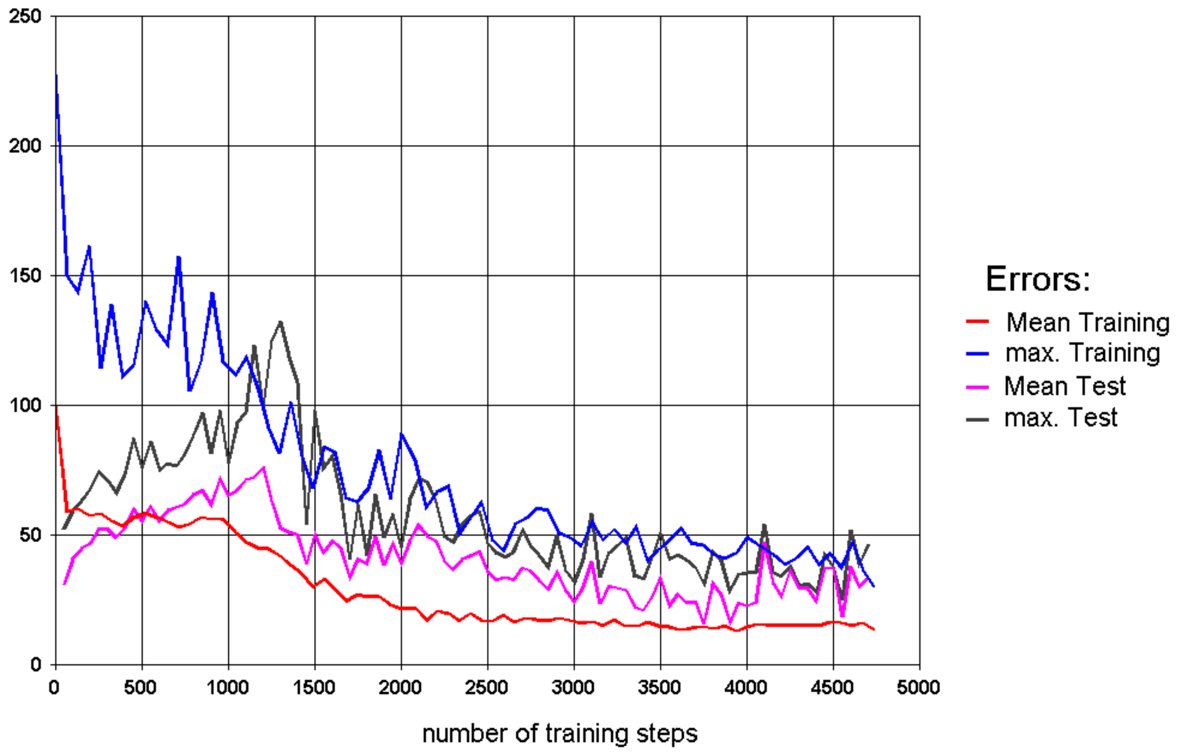

Figure 3 - Minimization of the training error by an iterative training process of the neural network.

In the second step, the trained network was tested with the competitions 26 and 27. On the basis of the testing the network parameters that allow the best fit were chosen. In the third and final step the optimized network was used to model the competitive performances of the 27 competitions and also of the last competition (#28). For the last modeling procedure, the neural network was provided with only the training input data. This forced the neural network to estimate the resulting competitive output data only on the basis of the formerly learned weights of the connected neurons on the three layers.

RESULTS AND DISCUSSION: The results of the modeling procedure demonstrate that after the thorough training procedure the backpropagation network is able to model the competitive performance from the two week taper phase (figure 4) by an average error of 16.8 LEN-points, that is 2.0 percent of the mean competitive performance of 820.9 LEN-points. Compared to the true competition times in the 400-m-freestyle (females) on the level of 821 LEN-points, that average error is equivalent to a deviation of 4:20.42 min plus 1,82 s or minus 1.5 s. The maximum error of the modeling is 39.7 LEN-points resp. 4.8 percent.

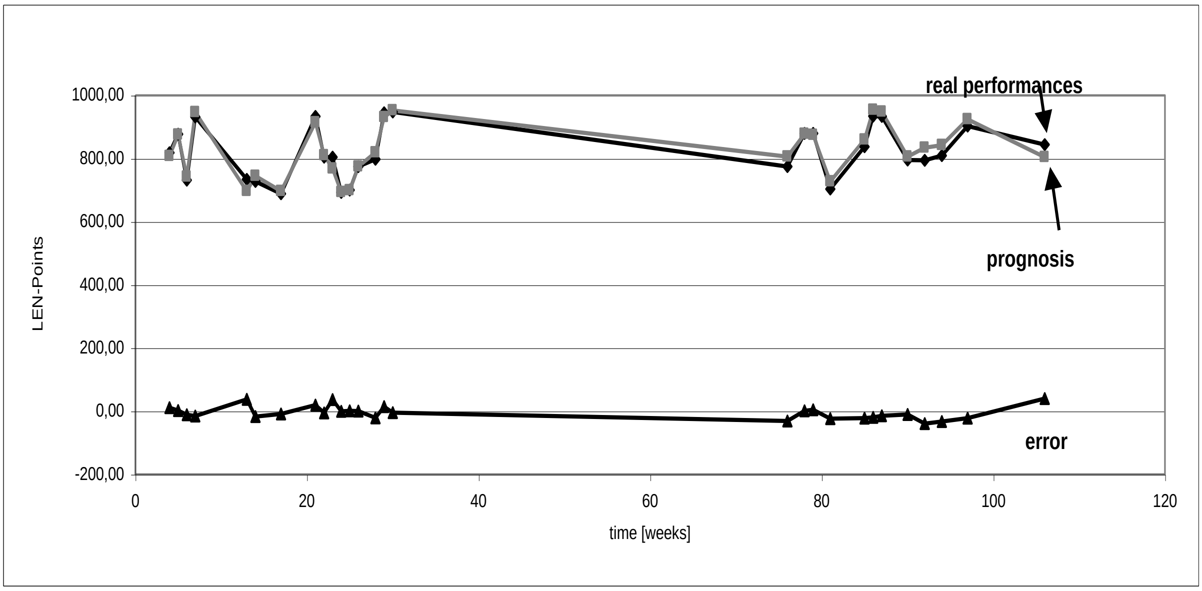

Figure 4 - Comparison of the real competitive performances and the performances modeled by a neural backpropagation network on the basis of the training data from the two-weeks taper phase.

The second modeling of the competitive performance output as adaptation effect of the high load training phase (figure 5) is less precise than the modeling of the effects of the taper phase. The average error of the modeling on the basis of the 10 different training volumes of the fourth and third week before the competition is 25.6 LEN-points. This is 3.1 percent of the mean competitive performance of 820.9 LEN-points. Such a difference is equivalent to plus 2.81 s or minus 2.69 s when swimming 4:20,42 min. The maximum error of the modeling is 96.8 LEN-points resp. 11.8 percent.

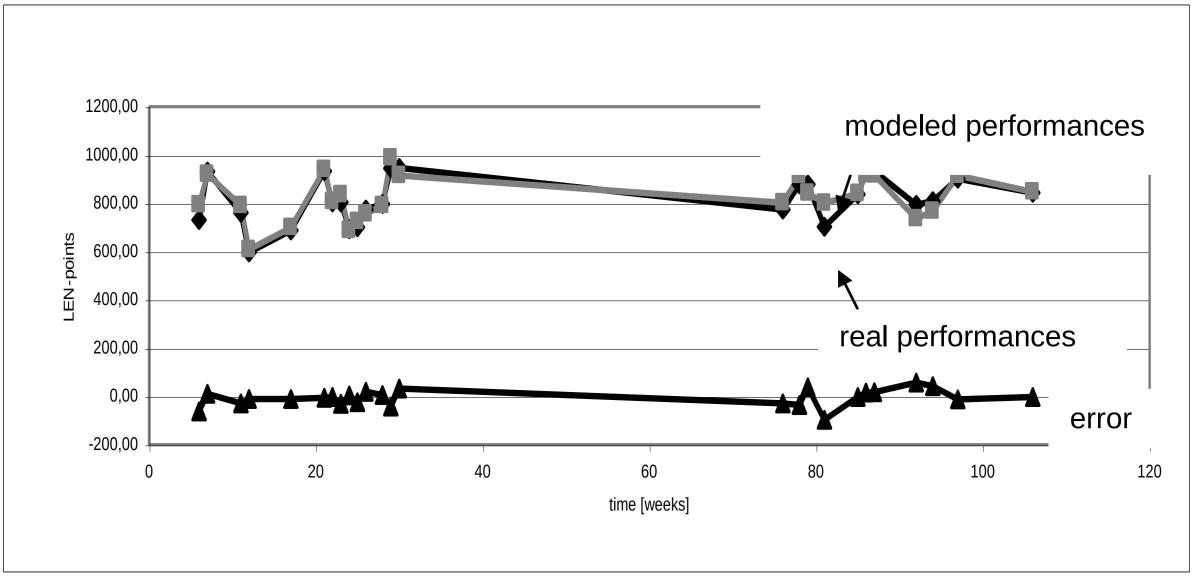

Figure 5 - Comparison of the real competitive performances and the performances modeled by a neural backpropagation network on the basis of the training data from the two-weeks high load training phase before taper

The precision of the neural network prediction is much higher compared to the prediction achieved by a conventional regression analysis (figure 6). To proof the advantage of the nonlinear approach to training analysis, a multiple regression analysis with ten predictors was calculated to quantify the effect of the taper phase. Therefore, the ten independent variables consisted of the training data in each of the five categories of training loads, that were recorded in the taper phase, that is the last week (week-1) immediately before the competition, and for the second last week (week-2) before the competition. So, the linear analysis was based on the same training input data as the nonlinear approach, when modeling the competitive performances as a result of the taper phase.

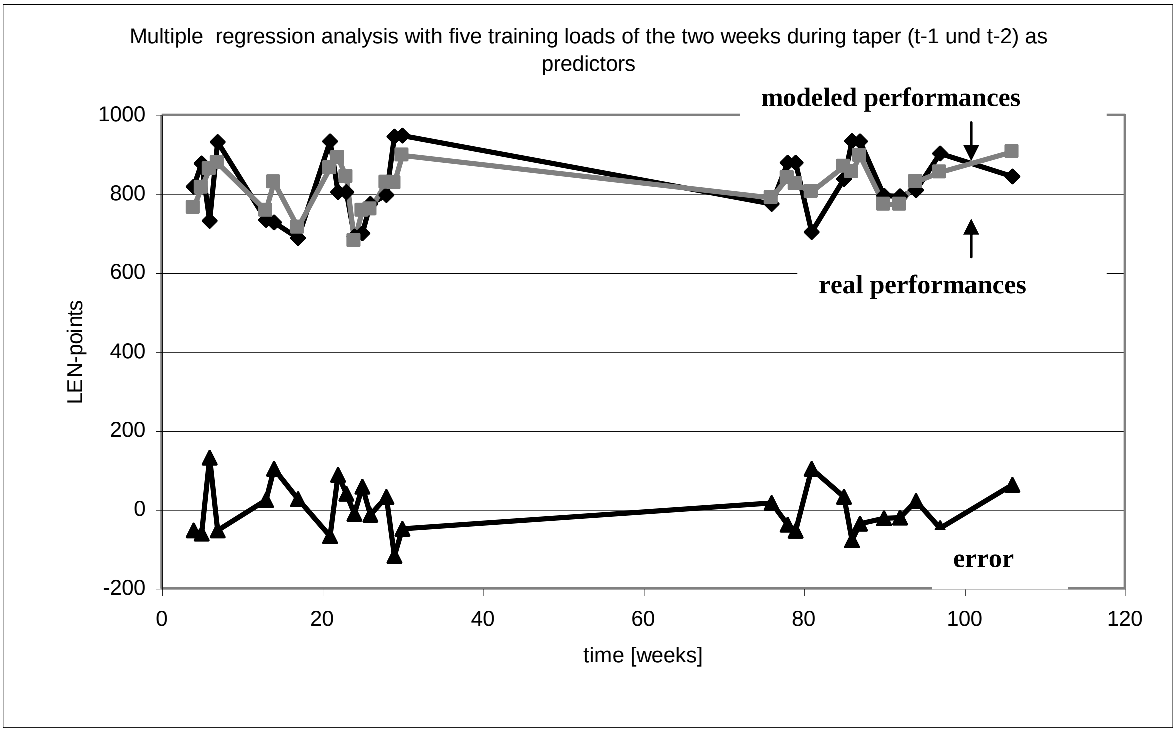

Figure 6 - Comparison of the real competitive performances and the performances modeled by a multiple regression analysis on the basis of the training data from the two-weeks taper phase

The results of the multiple regression analysis show an average error of the model prediction of the competitive performances by the training data of the taper phase of 52,2$\pm$32,4 LEN-points, that is 6.4 percent. Compared to the model prediction by the neural network method this is more than thrice as much. Related to the average of the real competition times in the 400-m freestyle of 4:20,42 min such an error leads to differences of plus 5.74 s or minus 5.28 s. The maximum error of the modeling is 131,3 LEN-points resp. 16,0 percent.

CONCLUSION: The results of the study demonstrate that neural backpropagation nets such as the used 'multilayer perceptron' are excellent tools to model and even prognose competitive performances on the basis of training data.

1. One of the main advantages of the neural network method is that the original training data recorded by the coach do not have to be transformed into an arbitrary 'training impulse' (Banister, 1982) or any other more or less artificial training load parameter. The application of the neural network method is even possible when the data basis resulting from the training record of the coach is inappropriate for advanced regression analysis. Real training data, although relevant for the practical field, very often is too small or not adequately scaled to allow scientific progress with the methods commonly used up to now.

2. Another advantage of the neural network method is that it can model linear and also nonlinear transformations of the training stimuli into performance, that take place in a single athlete. Nonlinear transformations are to be expected, when the system athlete changes itself within the investigated time period under the influence of training. The research conducted by Banister and the different groups of coworkers provides much evidence that, indeed, the adaptability of an athlete changes in the course of the training process. Banister (1982) stated in his study on swimmers that because of the changes in the ability both to absorb and respond to training stimulus, the modeling and the prediction of competitive performances by means of transfer functions (least square algorithms) is only then stable, when the training process does not last longer than 60 to 90 days. After that time period a new individual model fit has to be found. Therefore, the model parameters (e.g. decay time constants for fitness and fatigue, weighting of training intensity zones) have to be manipulated intuitively or by trial and error. Later investigations in swimmers by Fitz-Clarke, Morton, & Banister (1991) confirmed these results. Training impulses in a later stage of the same training process led to different adaptations in the variables fatigue and fitness.
3. Furthermore, the method is not only able to 'learn' the individual adaptative behavior of the athlete. After the learning procedure the neural network is also able to calculate a simulation of the prospective performance responses of the athlete under the influence of a slightly changed structure of the training input. So, after some training analysis the trained neural network allows the coach to simulate the effects of certain modifications of the training program on the competitive performance of the athlete. This makes the planning and monitoring of a training process more effective.
4. A fourth advantage of the neural network method is very important in respect to training theory. The higher quality of the results delivered by the nonlinear modeling of the training responses gives support to a synergetic approach to the analysis of training adaptation. From a synergetic point of view, the athlete can be described as a complex dynamic system. One idea is that the system athlete enters a certain stage of stability of performance (attractor) under the influence of the training load (control parameter). The neural network method can help to identify the optimal range of training load, that is necessary to help the system athlete to self-organize the transient state of optimal performance.

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