REVIEW ARTICLE

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The Analysis and Utilization of Cycling Training Data

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Contents

Abstract

Most mathematical models of athletic training require the quantification of training intensity and quantity or ‘dose’. We aim to summarize both the methods available for such quantification, particularly in relation to cycle sport, and the mathematical techniques that may be used to model the relationship between training and performance.

Endurance athletes have used training volume (kilometres per week and/or hours per week) as an index of training dose with some success. However, such methods usually fail to accommodate the potentially important influence of training intensity. The scientific literature has provided some support for alternative methods such as the session rating of perceived exertion, which provides a subjective quantification of the intensity of exercise; and the heart rate-derived training impulse (TRIMP) method, which quantifies the training stimulus as a composite of external loading and physiological response, multiplying the training load (stress) by the training intensity (strain).

Other methods described in the scientific literature include ‘ordinal categorization’ and a heart rate-based excess post-exercise oxygen consumption method.

In cycle sport, mobile cycle ergometers (e.g. SRM™ and PowerTap™) are now widely available. These devices allow the continuous measurement of the cyclists’ work rate (power output) when riding their own bicycles during training and competition. However, the inherent variability in power output when cycling poses several challenges in attempting to evaluate the exact nature of a session. Such variability means that average power output is incommensurate with the cyclist’s physiological strain. A useful alternative may be the use of an exponentially weighted averaging process to represent the data as a ‘normalized power’.

Several research groups have applied systems theory to analyse the responses to physical training. Impulse-response models aim to relate training loads to performance, taking into account the dynamic and temporal characteristics of training and, therefore, the effects of load sequences over time. Despite the successes of this approach it has some significant limitations, e.g. an excessive number of performance tests to determine model parameters. Non-linear artificial neural networks may provide a more accurate description of the complex non-linear biological adaptation process. However, such models may also be constrained by the large number of datasets required to ‘train’ the model.

A number of alternative mathematical approaches such as the Performance-Potential-Metamodel (PerPot), mixed linear modelling, cluster analysis and chaos theory display conceptual richness. However, much further research is required before such approaches can be considered as viable alternatives to traditional impulse-response models. Some of these methods may not provide useful information about the relationship between training and performance. However, they may help describe the complex physiological training response phenomenon.

Scientists examining exercise training have identified distinct roles for training volume, intensity and frequency in the adaptation process.[1] In order to optimize performance when working with elite athletes, it is essential that the sports coach has a thorough understanding of the relationship between training and performance. These relationships have been shown to be highly individualized due to variation in factors such as individual training background,[2] genetics[3] and psychological factors.[4] In order to further this understanding, a number of mathematical models have been developed in an attempt to describe the dynamic aspect of training and the consequences of successive training loads over time.[4-6]

1. Quantification of Training

Most mathematical models of athletic training require the quantification of training intensity and quantity or ‘dose’. Ideally, this quantification requires researchers to incorporate parameters for intensity, duration and frequency. Endurance athletes have used training volume (kilometres per week and/or hours per week) as an index of training dose with some success.[7,8] However, this index fails to accommodate the potentially important influence of training intensity. Therefore, a number of alternative methods have been investigated.

1.1 Session Rating of Perceived Exertion

The rating of perceived exertion (RPE) provides one method of subjectively quantifying the intensity of exercise.[9] Defined by the intensity of discomfort or fatigue felt at a particular moment, RPE has been shown to correlate well with intensity of effort.[10] In order to provide an index of a whole training session, Foster et al.[11] developed the session RPE (sRPE) scale as a modification of the standard RPE scale. Rather than providing an RPE score for a specific aspect (e.g. interval/set) of an exercise session, sRPE aims to provide an RPE for the session as a whole, i.e. to integrate the myriad of exercise-intensity cues.[10] The sRPE scale has been shown to be a reliable and valid method of quantifying intensity during both aerobic and resistance exercise when compared with heart rate-based metrics.[10,12,13]

1.2 Ordinal Categorization

Training has also been categorized into ordinal levels based on differences in intensity. Whilst this categorization has been arbitrary in some instances,[14] this approach is commonly based upon the relationship between a measured variable, such as speed, and heart rate[15] or lactate response.[2] Each category is then assigned an arbitrary weighting coefficient that emphasizes high-intensity training sessions. Being based upon an individual's physiological response and assuming a non-linear response to increasing exercise intensity, these methods appear more scientifically defendable. However, an element of subjectiveness remains due to the arbitrary weighting of intensity categories. Furthermore, using heart rate in the process of training quantification has a number of limitations. Irrespective of exercise intensity, heart rate may vary due to factors such as cardiac drift,[16] changes in temperature,[17] hydration status and body position on the bicycle.[16]

1.3 Heart Rate Recovery and Training Impulse

Overcoming some of the above limitations, Borresen and Lambert[18,19] have suggested that, as indirect markers of autonomic function, heart rate variability and, in particular, heart rate recovery may offer practical ways of quantifying the physiological effects of training. However, much further work is required before these methods can be shown to have practical application in the prescription of optimal training programmes.[19]

Training impulse (TRIMP) quantifies the training stimulus as a composite of external loading and physiological response, multiplying the training load (stress) by the training intensity (strain).[20] Banister and Calvert's[21] original formula was modified by Morton et al.[22] to include a multiplicative factor that gave greater weight to high-intensity training (equation 1):

$$\begin{aligned} \text{TRIMP} = {} & \text{exercise duration} \cdot \\ & \text{fraction of heart rate reserve} \cdot \\ & e^{(\text{fraction of heart rate reserve} \cdot b)} \end{aligned} \qquad \text{(Eq. 1)}$$

where e is Euler's number, 2.718, and b is a constant based on the blood lactate response during incremental exercise and is equal to 1.92 in males and 1.67 in females.

There are advantages to using the TRIMP method, evidenced not least by the number of researchers who have explored the use of this metric.[23-25] It is relatively easy to calculate TRIMP with an inexpensive and commonly used heart rate monitor. This approach produces a single number that represents the training stimulus provided by the whole session. However, the original Banister formulation of the TRIMP concept failed to take into account the energy system-specific effects of training intensity. Whilst, to some extent, Morton's weighting factor overcomes this shortcoming, it is still limited in assuming a fixed relationship between heart rate and lactate responses; an assumption that Hurley et al.[26] dispute.

1.4 Excess Post-Exercise Oxygen Consumption

Whilst sRPE and TRIMP have received support in the scientific literature, both methods are limited by a lack of underpinning physiological theory. In order to quantify the homeostatic disturbance associated with training, traditional physiological measures such as oxygen consumption, heart rate and blood lactate may be obtained. However, these latter measures only reflect a momentary response to exercise. Blood lactate concentration, measured during or post-exercise, might also depend on sampling site. In contrast, the measurement of excess post-exercise oxygen consumption (EPOC) has been suggested to reflect the cumulative response of the body to a whole training session. As with the measurement of oxygen uptake and lactate response, EPOC assessment is laboratory-based, expensive, time-consuming and, therefore, inappropriate for regular assessment. Recognizing this limitation, Rusko et al.[27] developed a heart rate-based EPOC (HR-based EPOC) prediction model, which is mathematically described as equation 2:

$$\mathrm{EPOC}_{(t)} = f(\mathrm{EPOC}_{(t-1)}, \%\ \dot{V}O_{2\max}, \Delta t) \quad \text{(Eq. 2)}$$

EPOC at time t ($\mathrm{EPOC}_{(t)}$) is estimated using the variables of current intensity ($\%\ \dot{V}O_{2\max}$), duration of exercise (time between two sampling points [Δt]) and EPOC in the previous sampling point ($\mathrm{EPOC}_{(t-1)}$). This model has been validated in a group of 32 healthy adult subjects, HR-based EPOC correlating well with measured EPOC ($r = 0.89$).[27] Mean absolute error values for the HR-based EPOC, when compared with the measured EPOC values, were 9.4, 14.0 and 16.9 mL/kg for 40% and 70% constant load exercise and for maximal incremental exercise, respectively. However, despite the attractiveness of this model, the calculation is relatively complex, currently requiring proprietary software and hardware (e.g. Suunto™ t6 heart rate monitor). In addition, the model has only been validated in one study, in which only short-duration exercise (2×10 min) was investigated.[27]

1.5 Power Output

Mobile cycle ergometers (e.g. SRM™ and PowerTap™) are now widely available and allow the continuous measurement of the cyclists' work rate (power output) when riding their own bicycles during training and competition. Indeed, in one study of these devices, the authors concluded, "measures with such low error might be suitable for tracking the small changes in competitive performance that matter to elite cyclists."[28] Consequently, these devices have been widely used by elite cyclists during training and competition. Thus, with such instrumented bicycles it is now possible to examine the completed training and race performances and associated physiological responses in detail. An example of typical data collected during a training bout is shown in figure 1. This ability to accurately quantify the mechanical work of training, as well as the detail and extent of these data, makes cycling unique in allowing such insight into the demands of sporting preparation and competition. However, it can also be seen that the inherent variability in power output during training poses several challenges in attempting to evaluate the exact nature of any training session.

As a result of the difficulties in interpretation of power output data, the current practice for many athletes and coaches is to simply visually inspect individual training sessions (e.g. as presented in figure 1). In this way, general features of the session may be identified, such as the point at which the highest power output was achieved, the number of intervals completed or the level of power output variation. Clearly, such methods fail to allow full analysis of the available data. An alternative approach is to evaluate the amount of time spent within given power 'bins' or 'zones' using a histogram. Ebert et al.[29] provided a graphical comparison of two types of women's World Cup cycle road races by evaluating the percentage of total race time spent within four power bins (0–100 W, 100–300 W, 300–500 W and >500 W). Recognizing the important influence of body mass on cycling performance, Ebert et al.[30] provided similar comparisons of power output per unit body mass (W/kg) in a group of professional male stage race cyclists. Although simple, this method is excellent for the purpose of overall session comparisons.[31] However, the histogram approach is limited by its inability to recognize separate efforts within any given power zone.

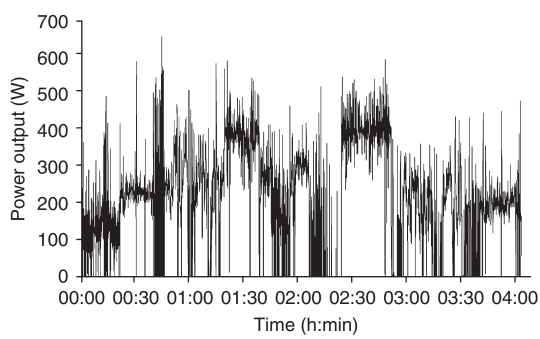

Fig. 1. Example of training power output data measured with an SRM™ crank system.

For example, this method is unable to differentiate between a single 5-minute effort at 350 W and five 1-minute intervals at the same intensity, although the effect of these two bouts of exercise on training outcomes may be very different.[32]

1.5.1 Average Power

Power output provides a direct and immediate measure of work rate, as opposed to the athlete's perceptual or cardiovascular response to that exercise intensity. However, as discussed in section 1.5, the stochastic nature of work rate when cycling outdoors[33] makes interpretation of information from on-bike power meters problematic. A simple approach is to calculate mean or average power over the duration of the training bout. However, average power is not necessarily commensurate with the cyclist's physiological strain unless the training session is constant power in nature. For example, a maximum effort in a 1-hour time-trial over flat terrain may result in a mean power of 299 W and require little variation in power output over the course of the race (figure 2a). In contrast, a maximum effort requiring marked changes of pace, e.g. in a criterium-type race or a hilly time-trial, may result in the rider being able to produce a much lower average of only 260 W (figure 2b). Future research should seek to describe in detail what the differences in overall power are for variable versus constant power cycling.

1.5.2 Normalized Power

Recognizing the limitations of the average power approach, Coggan[34] has proposed using an exponentially weighted averaging process to represent the data. Data are smoothed using a 30-second moving average (because many physiological processes [e.g. $\dot{V}O_2$, heart rate] respond to changes in exercise intensity with a time-constant of ~30 s) before being raised to the fourth power (derived from a regression of blood lactate concentration against exercise intensity). Finally, the transformed values are averaged and the fourth root taken, yielding a 'normalized power'. Using this process, it is theoretically possible to make more direct comparisons between different types

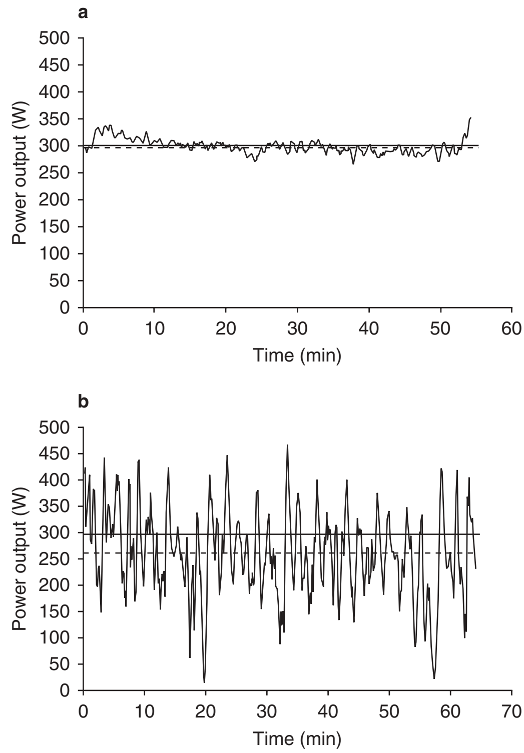

Fig. 2. 30-second rolling average for power for a flat time-trial (**a**) and a criterium road race (**b**) performed by the same cyclist. Note that average power (dashed line) varies widely between efforts, whilst the normalized power (solid line) is similar, indicating an equivalent physiological cost for both efforts.

of training sessions. In the above example, for instance, the time-trial effort normalized remains about 299 W (figure 2a), but the variable effort of 260 W normalized becomes 291 W (figure 2b). Whilst this method has attracted substantial interest from the cycling community, it has as yet received very little critical evaluation from the scientific community.[35]

1.6 Power Spectrum Analysis

The ability to move forward during cycling requires energy to overcome environmental resistance (principally wind, rolling and gravitational resistance[36]). Thus, variation in these resistive forces whilst cycling results in predictable changes in power output. However, beyond these physical relationships, Hu et al.[37] have suggested that 'other' fluctuations in data from biological systems represent 'noise', this being the result of either random processes or external input to the system. If this noise was the result of random factors, a power spectrum analysis would reveal a Gaussian white noise signal (i.e. where all frequencies have an equal power weighting).[38] Tucker et al.[39] used a discrete Fourier transform (DFT) in order to evaluate the power spectrum of the power output of amateur cyclists. A DFT expresses data as a sum of sinusoidal waveforms of varying frequency (figure 3), with the spectrum of the signal being the signal that describes the way in which the amplitudes and phases of these waveforms change with frequency. Therefore, at a specific frequency it is possible to obtain the measure of the contribution that a specific waveform will make to the signal. Using this method, Tucker et al.[39] demonstrated the presence of dominant frequency peaks (at distance cycles of ~2.5, ~6, ~12 and ~21 km) during a laboratory-based 20 km time-trial, suggesting that the observed power output fluctuations were in fact non-random. Tucker et al.[39] proposed that the fluctuations in power output were the result of the regulation of power output by intrinsic biological control processes. Differing dominant frequency spikes were also observed when analysing the frequency spectrum of individual components of the time-trial (i.e. beginning, middle and end) and the trial as a whole. Each of these dominant spikes was suggested to represent a different control system or component of an overall system. It would be interesting to investigate if such effects are repeated in a larger dataset and over longer periodicities (e.g. days, months) than those considered by these authors.

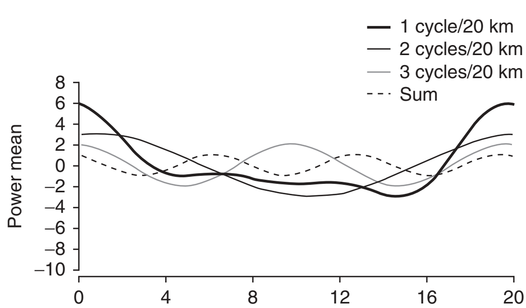

Fig. 3. An example of a Fourier transformation expressing the data as a sum of sinusoidal waveforms of varying frequency. In this example, three sinusoidal waveforms were added together to create a power signal that looks similar to the power output data observed during a 20 km time-trial (reproduced from Tucker et al.,[39] with permission).

Tucker et al.[39] also investigated the level of self-similarity in the time-trial power output signal of cyclists using a fractal analysis. In this context, the concept of self-similarity refers to the property that parts of the fractal signal are similar to the whole. Despite the large variability in power output generated both inter- and intra-trial, these authors found that the fractal dimension of the power spectrum was similar (1.56–1.9) in all subjects. Thus, despite the irregular power spectrum signal, there would appear to be a degree of self-similarity between parts of the signal and the signal as a whole. Tucker et al.[39] suggested that this signal concordance indicates a similar overall controlling process present in each cyclist and throughout each time-trial. Further research should seek to establish whether such findings reflect real physiological phenomena or, instead, if they simply reflect the widespread applicability of fractals.

2. Modelling the Relationship between Training and Performance

Models may be purely empirical or based on a detailed appreciation of the underlying structure.[20] Clearly, these underlying structures can be extremely complex. Whilst mathematical models are based on abstractions of the real system, the question remains of how much underlying structure to incorporate into models of training and performance.

2.1 Impulse-Response Models

Building upon early investigations by Banister et al.,[4] several research groups have applied systems theory to analyse the responses to physical training.[2,40,41] This approach attempts to abstract a dynamic process into a mathematical model, the system being characterized by at least one input and one output related by a mathematical 'transfer function'.[42] This function follows the general form (equation 3):

$$\text{Model performance} = (\text{fitness from training model}) - K(\text{fatigue from training model}) \qquad \text{(Eq. 3)}$$

where K is the constant that adjusts for the magnitude of the fatigue effect relative to the fitness effect.[20] Calvert et al.[14] presented a simple model whereby a single training impulse elicited two fitness responses that would increase performance and a fatigue response that would decrease performance. Thus, 'impulse-response' models aim to relate training loads to performance, taking into account the dynamic and temporal characteristics of training and, therefore, the effects of load sequences over time.

This model has been presented in a variety of mathematical forms, most notably the differential equations of Calvert et al.,[14] Morton et al.,[22] Busso et al.[43] Fitz-Clarke et al.[44] and Busso et al.[45] have built upon these formulations to present influence curves that provide a clear picture of how a specific training session affects performance at a future time. Indeed, Busso et al.[45] found that the positive and negative 'influences' (PI and NI) were actually closer to the variations in performance than the values calculated by the positive and negative functions (PF and NF) produced in the underlying mathematical model itself (i.e. where PF and NF represent an immediate fitness gain and PI and NI represent a more biologically plausible delayed fitness gain).

A variety of data types have been used as input in impulse-response type models. When predicting the performance of two non-elite runners, Morton et al.[22] quantified training impulse using TRIMPs. In one subject, agreement between measured and predicted performance was excellent ($R^2 = 0.96$), whilst in the second it was less impressive ($R^2 = 0.71$). Through the utilization of ordinal categorization of training, Mujika et al.[2] identified weaker relationships, with the explained variation in performance ranging from $R^2 = 0.45$ to $R^2 = 0.85$ in a group of elite swimmers. One proposed explanation for this variability is that model parameters change over time (i.e. with training). As such, Busso et al.[46] compared both a time-varying and a time-invariant model, with $R^2 = 0.88$ and $R^2 = 0.68$, respectively. However, the use of the model and its parameters to predict the responses to future training is precluded with the time-varying approach, unless the parameters change in a predictable manner.[20]

Impulse-response modelling provides pertinent information about interindividual differences and permits the construction of individualized training programmes[47] (e.g. TRIMP, TrainingPeaks WKO+ and RaceDay software). However, both the original Banister model and its extensions have some significant limitations. Taha and Thomas[20] argued that the model does not correspond with contemporary understanding of physiological mechanisms, requires an excessive number of performance tests to determine model parameters, and is unable to distinguish the specific effects of different training impulses. Furthermore, inter-study and inter-subject variability in parameter estimates limits the ability to apply a generic version of the model.

2.2 Neural Networks

Traditional impulse-response models such as those described in section 2.1 are based on linear mathematical concepts such as regression analysis and linear differential equations. However, because the adaptation of a biological system leads to changes in the system itself, biological adaptation is actually a complex non-linear problem.[48] For this reason, Edelmann-Nusser et al.[48] used a non-linear multi-layer perceptron neural network to model the performance of an Olympic-level swimmer. This model produced a 'prediction error' of just 0.04%.

One problem associated with neural networks is that they typically require many datasets to 'train' the model. Having ten input neurons, two hidden neurons and one output neuron, training of the model used by Edelmann-Nusser et al.[48] required 40 datasets (this number increasing to 60 with the addition of just one neuron in the hidden layer). Thus, it may be some time before such a model becomes useful for any given athlete. Edelmann-Nusser et al.[48] overcame this problem by training the model with the datasets of another athlete. Ultimately, this method proved to be successful, but, as noted by the authors, it may have been fortuitous that the adaptive behaviour of both athletes was similar. Although the predictive power is impressive, Hellard et al.[47] have cautioned that the major weakness of neural network models is that they don't explicitly identify causal relationships, i.e. they function as a 'black box'.

2.3 Dynamic Meta-Model

The Performance-Potential-Metamodel (PerPot) described by Perl[6] simulates the interaction between load and performance interaction by means of antagonistic dynamics. Hellard et al.[47] highlighted the conceptual richness of this model in that it accounts for the collapse effect in the wake of training overload, the atrophy associated with detraining and the long-term behaviour of the training-performance relationship.

Similar to the Banister model, the basic concept of the PerPot model is that of antagonism (see figure 4). Each load impulse feeds a strain potential as well as a response potential. These buffer potentials in turn influence the performance potential, where the response potential raises the performance potential (delayed by the delay in response flow) and the strain potential reduces the performance potential (delayed by the delay in strain flow). If the strain potential is overloaded an overflow is produced that has a further negative impact on performance potential. Whilst this model is attractive, to the authors' knowledge no researcher has yet provided a critical validation.

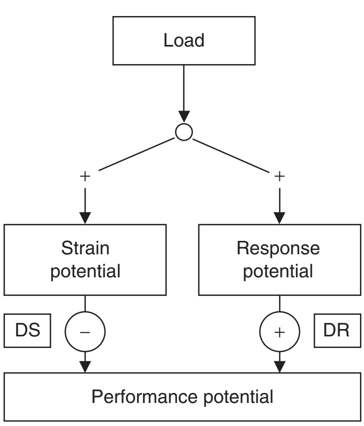

Fig. 4. Antagonistic structure of the Performance-Potential-Metamodel. **DR** = delay in response flow; **DS** = delay in strain flow.

2.4 Multiple Regression and Mixed Linear Modelling

As described above (section 2.1), one of the problems associated with the Banister model is the need for a very large number of datapoints per parameter. To ensure a stable solution in a regression analysis, Stevens[49] recommended a minimum of 15 observations per predictor variable. To avoid these difficulties multiple regression modelling has been suggested as a viable alternative, especially when relatively few repeated measurements are available for multiple subjects.[47] This method allows the integration of training loads as independent variables and can take the effects of load sequences over time into account. Mujika et al.[50] used a stepwise regression to create a model for the relationship between training and performance, reporting a very close match with the Banister model.

Mixed linear modelling can be applied to repeated measures data from unbalanced designs (i.e. multiple independent variables with unbalanced multiple levels on each factor). Unlike the Banister model, which produces a personal model for each subject, mixed models accommodate subject heterogeneity by allowing parameters to vary between individuals as a model of population behaviour is constructed.[5] Therefore, this type of analysis can also cope with the mixture of random and fixed effects that occur with 'real-world' data.[51] For example, performance-related data might be influenced by random fluctuations in environmental factors as well as systematic changes to training that are introduced by the coach. In general, all data are used to construct the part of the model common to the whole subject population whilst only the observations specific to each individual are used to construct the personal part of the model. The relative influence of each part of the model will therefore depend on the available data with a stronger contribution coming from the population data when the individual data is poor and *vice versa*.[5] Mixed linear modelling can also cope with missing data and 'nested' (hierarchical) models. A hierarchical model could be relevant to real-world research when, for example, subjects cannot be considered as being mutually exclusive, e.g. athletes who train with each other as part of a squad.

Mixed linear modelling has been employed to analyse psychological,[52] micro-array[53] and agricultural[54] data. However, this type of analysis has been little-used in the sport and exercise sciences. Indeed, where it has been used, it would not seem to have a strong predictive ability. Avalos et al.[5] found that mixed modelling did describe the relationship between training and performance but that the average coefficient of determination was just 0.38. Clearly, further work is necessary to ascertain the applicability of mixed modelling in a sporting context. An important issue, which needs careful consideration, is how the most appropriate covariance structure of repeated measures is identified and applied in mixed linear modelling.

2.5 Cluster Analysis

Cluster analysis has been used in a wide range of sporting contexts from the detection of banned substance use[55] to the analysis of weight transfer during a golf swing.[56] Indeed, cluster analysis may provide a useful tool in identifying group responses to training. Avalos et al.[5] investigated the relationship between short-, mid- and long-term training periods and performance using principal component and cluster analyses. Two principal component factors were identified with the cluster analysis providing statistical confirmation of the four distinct training responses based on these two components. The four training clusters identified a varying response (i.e. a combination of positive, negative or neutral reactions) to each of the three training periods independent of training load differences between subjects.

2.6 Non-Linear Dynamics and Chaos Theory

Chaos theory is one of a set of approaches for studying nonlinear phenomena. Specifically, chaos is a phenomenon that appears locally unpredictable but is in fact globally stable, exhibiting clear boundaries and displaying great sensitivity to initial conditions. A prime example of chaos in the human body is found in the beating of the heart.[57] The normal cardiac rhythm appears periodic. However, sensitive instrumentation has revealed that the normal heart rhythm shows small variability in the interval between beats.[58] This signal variance results from the interplay of the sympathetic and parasympathetic nervous systems, ultimately creating significant signal diversity and a complex and unpredictable heart rhythm.[59] The advantage of such aperiodicity is that the system is better equipped to adapt to changing demands. The heart also displays two additional characteristics of chaotic systems: the emergence of order[60] and the existence of strange attractors.[61]

While chaos theory has been applied to a range of biological phenomena,[62,63] to the authors' knowledge, this approach has yet to be considered in the context of training theory. From the preceding discussions, it is clear that the relationship between the multitudinous factors involved in training development is a dynamic non-linear problem. However, it is also probable that the constantly varying interactions between these factors create a predominantly stable oscillating system. The use of chaos theory to identify the key attractors (and the relationship between these attractors) in such a system might further inform our understanding of both individual and group training responses. Furthermore, chaos theory might describe the loss of system control associated with overtraining, a scenario analogous to the extensive studies of atrial fibrillation carried out using chaos theory.[64,65]

3. Conclusions

In this review, we have discussed the methods available to quantify training impulse in cycle sport and the methods available to model the relationship between this training impulse and performance. Many of the methods discussed are applicable across a wide range of sports; however, cycling is one of the few sports able to take advantage of the rich data provided by the continuous measurement of work rate (power output).

Individual training/competition bouts may be quantified using methods such as sRPE, TRIMP and HR-based EPOC. The measurement of power output enables sessions to be quantified in a number of ways that include histogram approaches, mean power output and 'normalized power' output. While different (useful) information is conveyed by each approach, further research should seek to provide a direct comparison of these methods.

A number of mathematical approaches have been used to analyse the responses to physical training. The use of impulse-response models has received substantial support in the scientific literature, whilst alternative approaches such as the PerPot metamodel and mixed linear modelling have yet to be fully explored. The type of analysis that a researcher/coach uses will depend upon the number of datapoints available, with the more complex models requiring more measurements being made over time. It is likely that some of the methods discussed here will not provide useful information when describing the relationship between training and performance. However, it is probable that some combination of these approaches, rather than any single model, will provide the best description of the complex physiological training response phenomenon.

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