Chapter 4

The contribution of load magnitude and number of load cycles to cumulative low-back load estimations: a study based on in-vitro compression data

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ABSTRACT

Cumulative low-back load is suggested to be associated with low-back pain, possibly due to (micro-)fractures of spinal segments. Based on available in vitro data it can be assumed that, in order to predict spine segment failure from cumulative compressive loading, load magnitude should be weighted with an exponent higher than one, whereas the number of cycles should be weighted with an exponent lower than 1. The aim of the present study was to assess both exponents based on available in-vitro data.

Data on loading to fatigue fracture of spinal segments under cyclic compression in-vitro were used and converted to survival probability for 5 load levels and 5 levels of number of cycles. Three optimization procedures were used to estimate the exponent of load magnitude and load cycles separately, and load magnitude and load cycles combined. Goodness of fit was assessed by comparing the Akaike's Information Criterion (AIC) between models.

The best fit, based on AIC and average error per data point was obtained with weighting of load magnitude and number of load cycles with exponents of approximately 2.0 and 0.2, respectively.

The results show that a combination of load magnitude and number of load cycles weighted with exponents of approximately 2 and 0.2 respectively provides a suitable measure of cumulative spinal compression loading. This finding may be of relevance for assessing cumulative low-back loads in studies on the etiology of low-back pain.

INTRODUCTION

High mechanical loads on the lower back during manual material handling have been associated with low-back pain (LBP; da Costa & Vieira, 2010; Lötters et al., 2003), possibly due to spinal segment (micro-)fractures (Marras et al., 1993; van Dieën et al., 1999). In addition to peak low-back loading, cumulative low-back load (CLBL) has been suggested to be associated with LBP (Kerr et al., 2001; Norman et al., 1998)
The most common way to calculate CLBL is a linear approach of integrating back load time series (F(t)) during a given period (Callaghan et al., 2001; de Looze et al., 1996; Marras et al., 2010; Norman et al., 1998):

$$\text{Load}_{cum} = \int_0^T F(t)\, d \qquad \textit{Equation 4.1}$$

which can be simplified to (Kumar, 1990):

$$\text{Load}_{cum} = \sum_{i=1}^{n} N_{cycles}(i) \cdot F(i) \text{ for } i=1,2,\ldots n \qquad \textit{Equation 4.2}$$

in which the (peak) low-back load magnitude of a given work task (F) is multiplied by the number of load cycles (N_{cycles}) of that work task, while these multiplications of all tasks during a work shift (n) are summed. However, it has been argued that high force has more impact on the increase in failure risk than in a high number of cycles (Brinckmann et al., 1988). For example, 15 cycles of 2000 N load would cause a higher risk than in 20 cycles of 1500 N. Thus, alternative calculations of CLBL have been suggested. For example, a linear approach after application of a low-pass filter to spinal loading time series has been suggested by Krajcarski and Wells (2008). Furthermore, non-linear calculations have been suggested as well, for example second order (Seidler et al., 2009; Seidler et al., 2001; Seidler et al., 2003) or fourth order weighting of load magnitude (Jäger et al., 2000), and polynomial calculated CLBL (Parkinson & Callaghan, 2007). Based on this diversity in CLBL calculations, it can be concluded that it is unclear yet how the magnitude of the low-back load contributes to CLBL. Moreover, to our knowledge, number of load cycles is to date always implemented linearly in measures of CLBL. However, visual inspection of in-vitro data (Brinckmann et al., 1988; Hansson et al., 1987; Rapillard et al., 2006) suggests that the contribution of number of load cycles is highly non-linear as well. The aim of this study was therefore to determine the contribution of low-back load magnitude and number of load cycles in CLBL calculations, based on risk of tissue failure. To this end, results of in vitro fatigue failure spine compression experiments of Brinckmann et al. (1988) were used.

METHODS

Analyses of the present study are based on data collected by Brinckmann et al. (1988) who conducted a compression fatigue loading protocol on seventy lumbar motion segments.

First, failure load was established by applying compression in one randomly selected motion segment from each spine until fracture occurred. The mean ultimate strength of all specimen was estimated to be 5.24 (2.07) kN, ranging from 1.80 to 10.40 kN. The remaining motion segments of each spine were tested cyclically in a fatigue testing protocol until fracture or to a maximum of 5000 cycles. For all cyclically loaded motion segments, we derived load level and number of cycles to failure from the original publication. Load range was expressed as a percentage of the predicted ultimate strength. All methodological procedures have been described in detail previously (Brinckmann et al., 1988).

Motion segments were classified into 5 groups based on the load range applied (20–30%, 30–40%, 40–50%, 50–60% and 60–70%). For each group we calculated the probability of survival (no fracture) after 5, 100, 500, 1000 and 5000 load cycles (Table 4.1). These data were transformed into data points by assigning the average survival probability after 5, 100, 500, 1000 and 5000 load cycles to all specimens that had been loaded in a specific load range (Table 4.2). To assess the exponents for load magnitude and number of load cycles in the calculation of CLBL, cumulative loading was defined as:

$$\text{Load}_{\text{cum}} = {N_{\text{cycles}}}^{N_{\text{exp}}} \cdot \text{Load}^{F_{\text{exp}}} \qquad \textit{Equation 4.3}$$

in which load magnitude is weighted with an unknown exponent (F_{exp}), and multiplied by the number of load cycles which is also weighted with an unknown exponent (N_{exp}). Since this load is hypothesized to be associated with the probability of survival, a linear relation between cumulative load and survival probability was assumed, so that survival probability can be expressed as:

$$\text{Survival probability} = \text{intercept} - \text{slope} \cdot ({N_{\text{cycles}}}^{N_{\text{exp}}} \cdot \text{Load}^{F_{\text{exp}}}) \qquad \textit{Equation 4.4}$$

Table 4.1 | Probability of a motion segment to survive without compression fracture depending on the relative load and the number of load cycles applied. The table is adjusted from Figure 16 of the original paper (Brinckmann et al., 1988). Note that this original figure shows probability of fatigue fractures whereas here we report survival probability.

Relative loads	Load Cycles				
	10	100	500	1000	5000
60-70% (n=11)	91	37	9	9	0
50-60% (n=13)	100	61	38	15	8
40-50% (n=21)	100	64	45	45	32
30-40% (n=11)	100	100	82	82	73
20-30% (n=12)	100	100	100	100	92

Table 4.2 | Data points obtained from the original data. The average survival probability after 5, 100, 500, 1000 and 5000 load cycles was assigned to all specimens that had been loaded in a specific load range. For example, for the rightmost two lowest cells of Table 4.1, 12 data points were created in which a mean load range of 25 (20–30%) resulted in 92% survival after 5000 load cycles and 11 data points were created in which a mean load range of 35 resulted in a 73% survival probability after 5000 load cycles. This conversion led to a total of 340 data points.

Average Load	Load Cycles	Survival Probability	Number of data points (n=340)
25	10	100	12
35	10	100	11
45	10	100	21
55	10	100	13
65	10	91	11
25	100	100	12
35	100	100	11
45	100	64	21
55	100	61	13
65	100	37	11
25	500	100	12
35	500	82	11
45	500	45	21
55	500	38	13
65	500	9	11
25	1000	100	12
35	1000	82	11
45	1000	45	21
55	1000	15	13
65	1000	9	11
25	5000	92	12
35	5000	73	11
45	5000	32	21
55	5000	8	13
65	5000	0	11

Three optimization procedures were performed using simulated annealing (Goffe et al., 1994) in Matlab (The Mathworks, Natick MA, USA), to calculate intercept, slope and exponent(s) that resulted in the best fit through the data points by minimizing the average absolute error of all data. With regard to the exponents, in the first optimization, F_{exp} was assessed while assuming that N_{exp} is 1. In the second optimization, N_{exp} was assessed while assuming that F_{exp} is 1. In the last optimization, both F_{exp} and N_{exp} were assessed. For the three procedures, the abovementioned exponents as well as the intercept and slope of the best fit were calculated. Average absolute errors were calculated, while the goodness of fit of all fits was assessed using Akaike's Information Criterion (AIC; Akaike, 1974). We used this criterion since it takes into account the higher number of degrees of freedom in the third fit compared to the first two fits. The fit with the smallest AIC is considered the fit with the lowest loss of information. To test for the robustness of the current results, a leave-one-out cross-validation (LOOCV) was performed. This was done by leaving one cluster of data points out of the original sample. Subsequently, exponents were calculated by the abovementioned optimization procedures, based on the remaining sample. These exponents were validated using the 'left out cluster' by calculating the difference in predicted survival probability and actual survival probability. This was repeated such that each cluster of data-points was left out once, while differences between actual and predicted survival probability were averaged over all repetitions.

RESULTS

The probability of survival of the 5 groups of specimen exposed to different load ranges (Table 4.1) was transferred into 340 data points (Table 4.2; Figure 4.1). The first optimization resulted in a F_{exp} of 1.7 (AIC = 1048.64, averaged error = 22.33, LOOCV = 25.00):

$$\text{Survival probability} = 85.5 - 1.4 \cdot 10^{-5} \cdot (N_{cycles} \cdot \text{Load}^{1.7}) \quad \textit{Equation 4.5}$$

The second optimization resulted in N_{exp} of 0.2 (AIC = 981.32, averaged error = 15.01, LOOCV = 18.28):

$$\text{Survival probability} = 100.0 - 2.6 \cdot 10^{-1} \cdot (N_{cycles}^{0.2} \cdot \text{Load}) \quad \textit{Equation 4.6}$$

The third optimization resulted in F_{exp} and N_{exp} of 2.0 and 0.2 (AIC = 948.02, averaged error = 11.53, LOOCV = 14.06):

$$\text{Survival probability} = 100.0 - 5.1 \cdot 10^{-3} \cdot (N_{cycles}^{0.2} \cdot \text{Load}^{2.0}) \quad \textit{Equation 4.7}$$

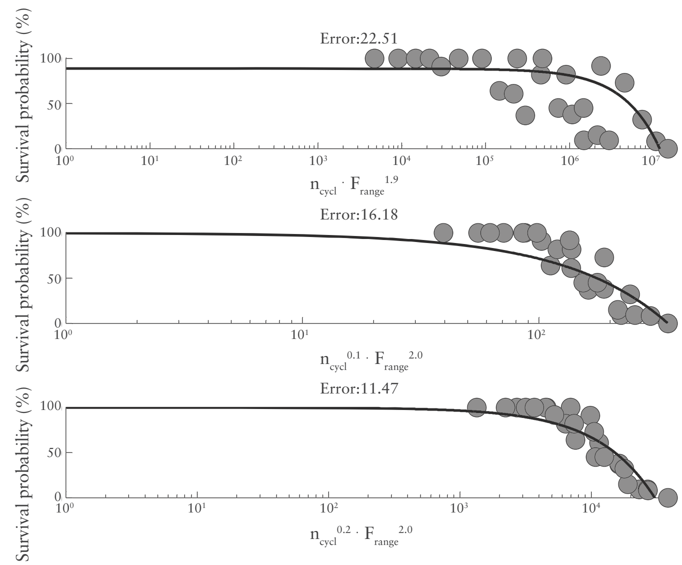

Figure 4.1 | Survival probability plotted against cumulative low-back load. Both the data points (dots) and the optimal fit of the function trough these data points (solid line) are shown. Furthermore, root-mean-square errors in comparison to the data points, averaged over data points are shown. An optimal fit through all data points assessing the relative weighting of load magnitude (upper panel), an optimal fit assessing the relative weighting of number of load cycles (middle panel) and an optimal fit assessing the relative weighting of both load magnitude and number of load cycles (lower panel) are shown. Note that each dot represents at least 11 and at most 22 data points. Dots are scaled to the number of data points they represent; the smallest dot represents 11 data points whereas the largest dot represents 21 data points.

DISCUSSION

The aim of the present study was to determine appropriate exponents for weighting of low-back load magnitude and the number of load cycles in CLBL calculations, based on in vitro compression data. Results show that weighting of load magnitude and number of load cycles with exponents of approximately 2 and 0.2 respectively can be suitable for CLBL estimates:

$$\text{Load}_{cum} = N_{cycles}^{0.2} \cdot \text{Load}^{2} \quad \textit{Equation 4.8}$$

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This can be rewritten to:

$$Load_{cum} = (N_{cycles} \cdot Load^{2/0.2})^{0.2} \qquad \textit{Equation 4.9}$$

which allows, due to the fact that N_{cycles} is now linear within brackets, summation of multiple (n) load levels, thereby making the equation applicable to work situations with multiple tasks of different load magnitudes:

$$Load_{cum} = (\sum_{i=1}^{n} N_{cycles}(i) \cdot F(i)^{10})^{0.2} \quad \text{for } i=1,2,\ldots n \qquad \textit{Equation 4.10}$$

And in fact, this equation can be simplified to:

$$Load_{cum} = (\sum_{j=1}^{k} F(j)^{10})^{0.2} \quad \text{for } j=1,2,\ldots k \qquad \textit{Equation 4.11}$$

where k is the total number of load cycles, that can be summed irrespective of the question whether or not some of them have equal load levels.

Both errors and AIC show a substantial reduction of the information loss in the third fit compared to the first two fits. These results suggest a substantial improvement of the estimation of CLBL when, in addition to exponentially weighting of load magnitude, the number of load cycles is exponentially weighted as well. It should also be noted that a weighting of load magnitude alone resulted in an intercept that deviated from the expected 100% survival at zero cumulative loading. Furthermore, as the LOOCV provides values that are only slightly higher than the calculated averaged absolute errors, it can be concluded that the present findings are robust.

These findings might have important implications for the calculation of CLBL. Concerning the earlier example about the risk of 15 times a 2000 N load compared to 20 load cycles of 1500 N, CLBL of these protocols will lead to $15^{0.2} \cdot 2000^2 = 6.87 \cdot 10^6$ and $20^{0.2} \cdot 1500^2 = 4.20 \cdot 10^6$ loads, a substantial difference in CLBL between the two protocols. This contrasts with the commonly used linear weighting of load magnitude and number of load cycles, which would result in equal CLBL estimates for these two protocols. Moreover, the method we propose might also be applicable to more realistic work situations. For example, combining the two abovementioned work situations might, according to Equations 4.10 lead to a CLBL of $(15 \cdot 2000^{10} + 20 \cdot 1500^{10})^{0.2} = 6.97 \cdot 10^6$. Not taking weighting of the number of load cycles into account can lead to large overestimations in the calculation of CLBL, as when only using the squared weighting of the load magnitude, this would yield a total CLBL of $15 \cdot 2000^2 + 20 \cdot 1500^2 = 1.05 \cdot 10^8$, a more than fifteen-fold higher estimate of the CLBL compared to our method.

It should be noted here that our analyses were performed, based on compression loads that were normalized to the ultimate strength of a specimen rather than on absolute data (N). Application of the current method to comparisons between (groups of) workers, concerning cumulative low-back loads or estimations of survival probability (based on

Equation 4.7 and the average ultimate strength of 5.24 kN this would for abovementioned example yields: $100 - 5.1 \cdot 10^{-3}(15 \cdot (100 \cdot 2000/5240)^{10} + 20 \cdot (100 \cdot 1500/5240)^{10})^{0.2}$ = 87% survival probability), would thus preferably take the capacity of the workers into account, for instance through prediction of individual ultimate strength (Brinckmann et al., 1988) as can for example be predicted in vivo using ultrasound (Nicholson & Alkalay, 2007).

The squared weighting of load magnitude in our best fitting model is consistent with the values proposed by Seidler et al. (2009; 2001), but not consistent with more conventional, linear weighting (e.g., Kumar, 1990; Marras et al., 2010; Norman et al., 1998) or a fifth order polynomial calculated by Parkinson and Callaghan (2007). In the latter study only material of healthy porcines was used instead of humans. Furthermore, no resulting errors were reported, making the results hard to compare to the present data. Besides, in our study, adding a weighting of number of loads turned out to lead to substantial improvement of the CLBL estimation.

It should also be noted that specimens in this study were exposed to one specific cycle time and load magnitude and that the number of load cycles was limited to a maximum of 5000. Whether the present results hold for other exposures (e.g. long sustained exposure or multiple different cyclic exposures), remains to be investigated. Furthermore, specimens in the current study were exposed to compression loads only, while in real life situations loading patterns are more complex and often occur in non-neutral postures (Kingma et al., 2006; Marras et al., 2010). However, compression loading is widely accepted as an important component of low-back loading (Potvin, 1997; van Dieën et al., 1999; Waters et al., 1993).

The choice to use average absolute errors rather than other possible calculations of errors (e.g., RMS errors) is an arbitrary one. However, when re-running our analysis using RMS instead of absolute average errors, we found a similar pattern of errors over optimizations and exponents that only slightly deviated for optimization 1. A limitation of the present study is that we used a multiplicative exponential model only. While we showed that this multiplicative model leads to robust outcomes, other functions may also result in acceptable fits. Furthermore, analyses were performed on data obtained from in-vitro measurements. Therefore, results might not generalize to in vivo situations. Cadaver material, certainly when not tested in a fluid bath does recover poorly from loads and biological repair is definitely absent. So the present study only applies to short term fatigue fracture loading (van der Veen et al., 2005). Roughly, repair of micro-fractures can be estimated to take several weeks. Results of the present study are therefore valid only within this interval.

CONCLUSIONS

It can be concluded that weighting compression forces and number of load cycles with exponents of approximately 2 and 0.2, respectively, provide a suitable metric of cumulative compression loading of the spine for conditions tested in this study. These findings might be relevant for future studies on LBP etiology.