MULTILEVEL MODELLING NEWSLETTER

Centre for Multilevel Modelling

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Software Review

The Centre for Multilevel Modelling is developing a comprehensive set of reviews of software packages for multilevel modelling.

The first set of reviews is now nearing completion. You can view the reviews completed so far at:
http://multilevel.ioe.ac.uk/softrev/index.html

A summary of completed reviews will be included in a future newsletter.

Forthcoming Workshops

27-29 October 2003, a three-day introductory workshop to multilevel modelling using *MLwiN* will take place at the Institute of Education.

This workshop can be booked on-line:
http://multilevel.ioe.ac.uk/support/workshop.html

Enquiries to Amy Burch at Centre for Multilevel Modelling, Institute of Education, 20 Bedford Way, London WC1H 0AL, United Kingdom. Tel: +44 (0) 20 7612 6688, Fax: +44 (0) 20 7612 6572, email: a.burch@ioe.ac.uk.

If you plan to run any workshops using *MLwiN*, please notify Amy Burch and she will advertise these workshops on the multilevel web site.

Fourth International Amsterdam Conference on Multilevel Analysis

The Fourth International Amsterdam Conference on Multilevel Analysis was held in Amsterdam on 28-29 April 2003.

The following papers were presented:

Multilevel Structural Equation Models: the Limited Information and the Two-Step Approach.
Hox, J. J., and Maas, C. J. M.
j.hox@fss.uu.nl

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Multilevel Factor Models for Ordinal Variables.
Grilli, L, and Rampichini, C.
grilli@ds.unifi.it

An MCMC Algorithm for Problems Involving 'Constrained' Variance Matrices with Applications in Multilevel Modelling.
Browne, W. J.
william.browne@nottingham.ac.uk

Incorporating Genetic Effects into Multilevel Models.
Rasbash, J.
j.rasbash@ioe.ac.uk

Analysing Student Progress in Higher Education using Cross-classified Multilevel Logistic Models.
Bell, J. F.
bell.j@ucles.org.uk

Marginal and Mixed Models: Using SUDAAN for Multilevel Analysis.
Shah, B. V.
shah@rti.org

Comparison of Methods in Regression Analysis with Correlated Data: A Simulation Study.
Shafer, L. A., Rice, J., Myers, L., Lefante, J., and Todd, J.
lshafer@tulane.edu

The Consequence of Ignoring a Level of Nesting in Multilevel Analysis.
Moerbeek, M
m.moerbeek@fss.uu.nl

The Effects of Poverty and Neighbourhood Characteristics upon Child Outcomes: Multilevel Analysis of Longitudinal Data.
Jones, C.
cjones@chass.utoronto.ca

The Impact of Clinical Lameness on the Milk Yield of Dairy Cows.
Green, L, et al.
laura.green@warwick.ac.uk

Effect of Pregnancy on HIV Disease Progression in Rural Uganda.
Van der Paal, L, Shafer, L. A., and Whitworth, J.
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Multilevel Model Diagnostics using MLwiN.
Snijders, T. A. B.
t.a.b.snijders@ppsw.rug.nl

Robust Outlier Detection in Multilevel Analysis.
Garza-Jinich, M
mgjinich@yahoo.com

Performance of Empirical Bayes Estimators of Random Coefficients in Multilevel Analysis: Some Results for the Random Intercept Only Model.
Candel, M. J. J. M
math.candel@stat.unimaas.nl

Testing for Homogeneity in Two Level Random Effects Models.
Bottai, M. and Orsini, N
matteo.bottai@cnuce.cnr.it

Derivation of Expected Mean Squares for Mixed-Effects ANOVA through the Use of Hierarchical Linear Modelling.
Liu, X.
xliu@gwm.sc.edu

Generalised Multilevel Survival Analysis.
Skrondal, A., and Rabe-Hesketh, S.
anders.skrondal@fhi.no

A Multivariate Multilevel Discrete-Time Hazard Model for Familial Aggregation and Co-Aggregation of Psychiatric Disorders.
Stolar, M.
marilyn.stolar@yale.edu

Diagnostics for Multilevel Models with Discrete and Categorical Responses.
Rabe-Hesketh, S.
spaksrh@mailbox.iop.kcl.ac.uk

A Model Building Approach for Endogenous Ordered Category Multilevel Analysis.
Spencer, N., and Fielding, T.
n.h.spencer@herts.ac.uk

Comparing Multiple Repeated Measurements of Aggression in Adolescent Boys: A Multilevel Perspective.
Plewis, I.
i.plewis@ioe.ac.uk

A Multivariate Multilevel Procedure for Correlated Changes.
Ma, X.
xin.ma@ualberta.ca

Modelling Short-Term and Long-Term Change Processes Using 'Nested' Growth Curve Models.
Zimprich, D., and Aartsen, M.
d.zimprich@psychologie.unizh.ch

Power Comparison of Completely and Stratified Randomised Designs in Cluster Randomised Trials: A Simulation Study.
Lewsey, J.
james.lewsey@stonebow.otago.ac.nz

Some Design Problems with Multilevel Data

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Introduction

'At the present time there appears to be little empirical or theoretical work on issues of optimum design for multilevel models,' (Goldstein, 1995, p.154). In the same book, (p.162) Goldstein wrote: ' … the issue of design efficiency has hardly been explored at all although it is an important topic practically.' In the subsequent eight years only a limited amount of work has been published on design issues with multilevel data, and much remains to be done.

First, to illustrate the work that has in fact been published since Goldstein's 1995 book, we outline briefly four of the relevant papers. Then we give an account of some recent work on design issues in an industrial experiment concerned with engine mapping in vehicle manufacture.

Some references

Mok (1995) considers a two level educational survey with data from I students in each of J schools. For each of the T=IJ students there is a dependent variable y (examination performance) and a single explanatory variable x (attitude toward achievement). The values x_{ij} and y_{ij} are assumed to follow a random slope model with six parameters (intercept, slope, level-1 variance, level-2 variances and covariance). 'Design' here is a choice of I and T/I = J, both for given T and for T at choice. Mok calculates estimates of the six parameters and bases conclusions regarding optimal design on the estimated sampling variances and biases of these estimates. No account is taken of cost factors.

Moerbeek et al. (2000) discuss design issues in the context of a treatment versus control three level experiment carried out on students within classes within schools. The treatment is a smoking prevention programme, the response y is a smoking behaviour measure, and the single explanatory variable x is binary (treatment or control). Three design issues are dealt with: the optimal level of randomisation; the optimal allocation of units, given a certain budget for sampling and measuring; and the budget required to obtain a certain power on the test of no treatment effect. The treatment effect is measured by the regression coefficient of y on x, and for optimal design this is to be estimated as efficiently as possible, i.e. the variance of the estimated regression coefficient is to be minimised. Results are obtained with relatively light calculation.

Moerbeek et al. (2001) discuss optimal design for a two level experiment with a binary response. The context is a veterinary medicine experiment, where sick animals within farms receive either control or the new treatment, with binary response recovered/not recovered, and single binary explanatory variable. A multilevel logistic model is assumed. The paper resembles Moerbeek et al. (2000) in the choice of design issues and the criterion of optimal design, but the computational effort required is now substantial and is given extensive discussion.

Liski et al. (1996-97) consider the situation where the expected value of a response variable Y depends on a single explanatory variable x, E(Y|x) = η(x), a regression function of assumed form with unknown coefficients. It is required to estimate the value x_0 of x at which η(x) attains a specified value y_0. The design issues are presented in the context of a practical problem in the logging industry. For a tapering vertical tree stem with diameter y at height x above ground, y and x are assumed to follow a random coefficient regression model. Diameters y_1, …., y_n are measured at heights $x_1,\ldots,x_n$. The design problem is to choose the number of observations *n* and the stem heights $x_1,\ldots,x_n$ to achieve optimal estimation of x_0, the height at which the stem diameter has a specified value y_0. The criterion for optimality is the estimated variance of $\hat{x}_0$.

Holliday's Engine Mapping Experiment Revisited

We conclude with a description of some recent work by Goldstein and Lewis on design issues in an industrial experiment to do with engine mapping in car manufacture. Engine mapping is the modelling of engine behaviour as a function of adjustable engine parameters. For our purposes these parameters are the following three:

Speed R - the speed at which the engine is turning.

Load L - the amount of air entering the combustion chamber on each intake stroke.

AFR (air/fuel ratio) A - the ratio of the airflow rate to the fuel flow rate.

Experiments are carried out to relate some chosen measure of engine performance - for our purposes, the maximum torque - to these factors R, L and A. The aim is to produce tables, which one enters with values of R, L and A and reads off the estimated maximum torque (or whatever).

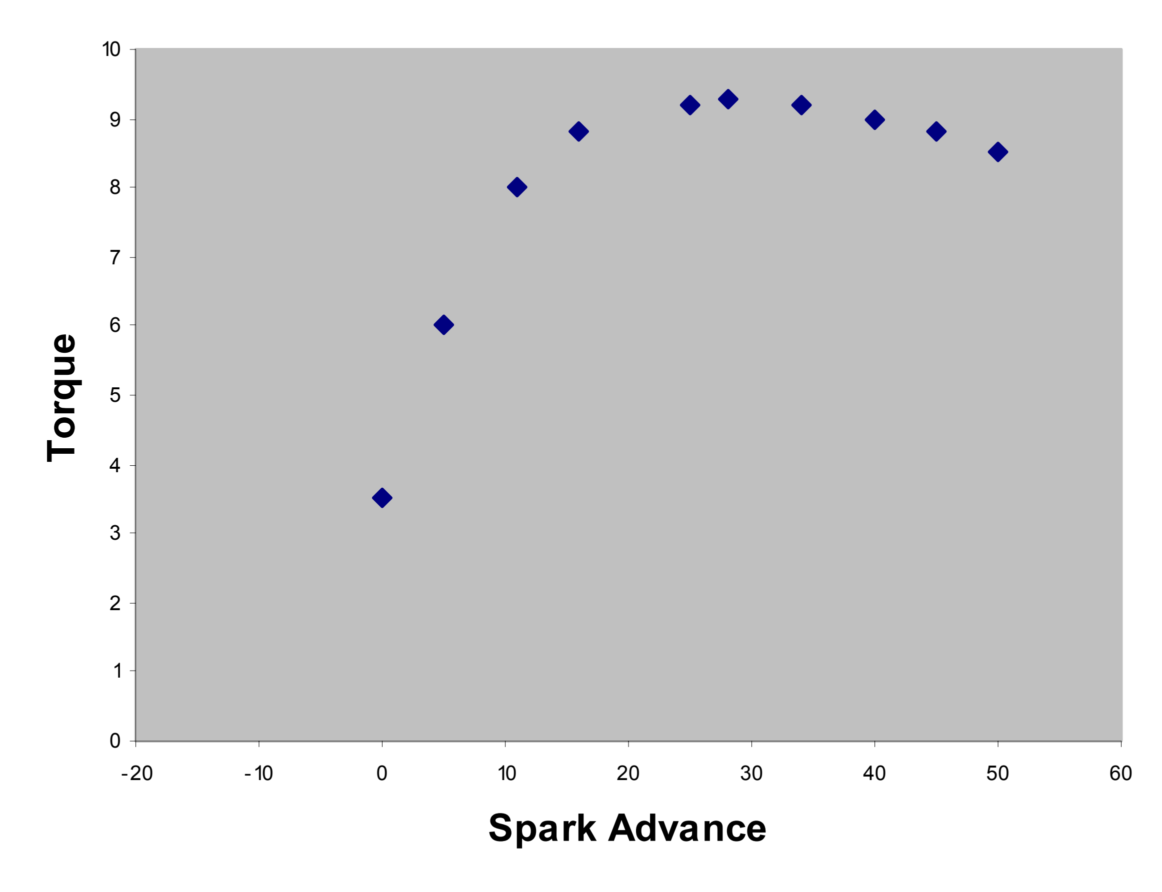
We have analysed - or rather, re-analysed - a well known data set from such an experiment (Holliday, 1995; Holliday et al., 1998). Holliday's data set has become quite a classic in the automotive industry, rather like Beveridge's wheat price index series or Fisher's iris versicolor and iris setosa or Brownlee's stackloss data.

The experiment has a two level repeated measures structure. The level-1 units are observations of engine torque at successive values of spark advance at constant R, L and A. Spark advance is the angle of rotation of the crankshaft when the spark is fired, measured in degrees relative to when the piston is at the top of the cylinder (positive when the piston is travelling up the cylinder, negative when it is travelling down). In the experiment, R, L and A are held constant and a sequence of 10 observations of torque is made at 10 successive values of spark advance. Such a set of 10 is called a *spark sweep*. The spark sweeps are the level-2 units.

In the experiment, 27 spark sweeps were carried out, with factor levels

R = 0, 1, 2 (actual values 1000, 3000, 5000)
L = 0, 1, 2 (actual values 0.2, 0.4, 0.6)
A = 0, 1, 2 (actual values 11:1, 13:1, 14.5:1).

Figure 1. A Typical Spark Sweep with R = 0, L = 0, A = 1



Within each spark sweep, as typified by the spark sweep in Figure 1, the torque rises to a maximum and then falls over the range of observed values of spark advance, denoted s. We use as a measure of the engine's ability to do work the transformed quantity 100 * ln(torque), denoted t, and assume a parabolic relationship between t and s within a spark sweep. Denote the maximum value of t on this parabola by y:

$$y = 100 * \ln(\text{max torque}) = t_{\max}$$

We take y as our measure of engine performance for given R, L and A, and we aim at modelling y in terms of R, L and A from the results of the 27 spark sweeps. The design issue is to use these results to reduce the amount of data and hence of future experimentation, which would be required for effective mapping over the ranges of practical interest of the parameters.

We model (s_{ij}, t_{ij}), the i^{th} observation (i = 1,…,10) in the j^{th} sweep (j = 1,…,27) as follows:

$$t_{ij} = \beta_0 + \sum_{h=2}^{27} \beta_h \gamma_{hj} + \alpha_{1j} s_{ij} + \alpha_{2j} s_{ij}^2 + e_{ij} \quad (1)$$

$$\underset{\sim}{\alpha} \sim \text{MVN}(\underset{\sim}{\mu}, \Sigma)$$

$$e_{ij} \sim \text{N}(0, \sigma_e^2)$$

This model fits a separate intercept for each sweep since the distribution of the mean torque does not follow any easily recognisable distribution. Table 1 gives the parameter estimates.

Table 1. Parameter Estimates (SDs)

β_0	= 260 (12)
μ_1	= 4.2 (0.66)
μ_2	= -0.064 (0.008)
$\sigma_1^{\ 2}$	= 11 (3.1)
σ_{12}	= -0.12 (0.034)
$\sigma_2^{\ 2}$	= 0.0014 (< 0.001)
$\sigma_e^{\ 2}$	= 39 (3.7)
$\hat{\rho}$	= -0.98

Hence we obtain a fitted parabola for spark sweep *j*

$$t_{ij} = a_j + b_j s_{ij} + c_j (s_{ij})^2 \quad (2)$$

with maximum height

$y_j = a_j - (b_j)^2 / 4c_j$ at spark advance

$$x_j = -b_j / 2c_j \quad (3)$$

The estimated values y_j from (3) are then used as responses in a 3-way (3x3x3) analysis of variance for the three factors R, L and A. In this analysis, shown in Table 2, the main effect for R on two degrees of freedom has been partitioned into a linear and a quadratic R-effect, each on one degree of freedom, denoted respectively R_l and R_q; similarly for L_l, L_q, A_l, A_q.

Table 2. Analysis of variance of the 3 x 3 x 3 y-values

	Sum of squares	df		Sum of squares	df	
R_l	2538	1	$R_l * L_l$	2288	1	
R_q	851	1	$R_l * L_q$	397	1	
L_l	167042	1	$R_q * L_l$	384	1	
L_q	10288	1	$R_q * L_q$	67	1	
A_l	83	1	$A_q * L_l$	37	1	
A_q	62	1	Residual	88	15	mean square 5.9
			Total	184125	26	

In Table 2, the first order interactions between R and A are non-significant at 5% and have been included in the residual; likewise the three first order interactions $A_l * L_l$, $A_l * L_q$, $A_q * L_q$. To interpret the various main effects and first order interactions, the mean responses at each of the 3 levels of R and L and at each of the 9 levels of R * L are shown in Table 3, with the three levels of R and L denoted 0, 1, 2.

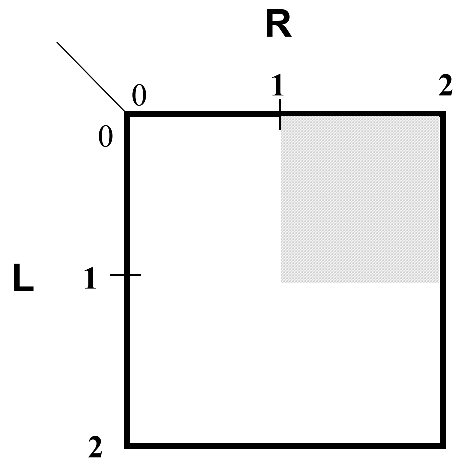
Table 3. Means of transformed maximum torque values y

		R			
		0	1	2	all R
L	0	226	221	168	205
	1	346	348	335	343
	2	398	401	395	398
	all L	323	323	299	315

Regarding the experiment as a pilot for setting up tabulations of y for practical use, with entry values of R, L and A covering the ranges sampled in the pilot (R, L and A each from 0 to 2), what can be said about its design?

Table 3 makes it clear what feature of the data gives rise to the significant R * L interactions shown in Table 2. The mean response is much the same for R = 1 as for R = 0 at all three levels of L, but for R = 2, it is significantly less than for R = 1 at L = 1 (335 vs. 348) and very significantly less at L = 0 (168 vs. 221). Thus the response varies substantially over the part 1 < R < 2, 0 < L < 1 of the (R, L) parameter space 0 < R < 2, 0 < L < 2, shown in Figure 2 as a shaded square. But we do not know the nature of the variation, since this part of the parameter space is unexplored by the experiment. For all we know, the decrease in y at L = 0 could occur near R = 1, or near R = 2, or in any pattern of change from R = 1 to R = 2. A revised experiment is required, which has been designed to explore this part of the parameter space.

Figure 2. The (R, L) parameter space



So for our next pilot, giving improved coverage of the ranges of R, L and A, we could have an experiment with just 25 spark sweeps, carried out at levels of R (say)

R = 0, 1, 4/3, 5/3, 2

combined with levels of L (say)

L = 0, 1/3, 2/3, 1, 2

Five values of A would also be included, say the following:

A = 0, ½, 1, 3/2, 2

But the advantage now is that only one level of A needs to be tested at each R * L combination, since there is no significant R * L * A interaction. So instead of a three way (3 x 3 x 3) analysis of variance for the three factors R, L and A, as in Table 2, we would now carry out three separate 2-way (5 x 5) analyses of variance, one for each pair of factors R and L, R and A, L and A – a further improvement in design.

Conclusion

The final words of my talk at the Canberra conference:

So there we are. Don't rack your brains to think up topics for your PhD students' theses – persuade them to do some research on design problems with multilevel data!

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Acknowledgements

This is in most part a shortened version of a talk given at the 16th Australian Statistical Conference, Canberra, July 2002.

I am most grateful to Professor Harvey Goldstein for his unfailing help and encouragement. With regard to the engine mapping problem, I would like to thank Dr Antony Fielding, Dr Dan Grove and Dr David Stevens for helpful discussions, and most particularly Professor Anthony Lawrance for advice and for providing the data and other indispensable material.

Review of 'Hierarchical Linear Models: Applications and Data Analysis Methods: 2nd Edition'. Advanced Quantitative Techniques in the Social Sciences Series 1. Raudenbush, S. W., and Bryk, A. S. Mahwah NJ: Sage ISBN: 0-7619-1904-X, pp. 486.

Dougal Hutchison

National Foundation for Educational Research

Also published in Educational Research, Volume 45, Issue 3

This book represents the long-awaited second edition of this text, first published in 1992, but it is not simply an updating of an old favourite. It is nearly twice as long as its predecessor, and while the first part of the book corresponds with an updated and extended version of the first edition, there are four completely new chapters. Those whose knowledge of MLM has stopped at the original application to schools will be amazed at the directions in which the technique has developed since then. Further, this edition at least has an index, obviously the authors have managed to overcome Sage's long-running distaste for this type of information. It would be difficult, in the space of a relatively short review, to cover all of the new topics and approaches described, and I shall just outline some of the most important.

Chapter 5 deals with what the authors describe as Applications in Organisational Research. This will probably be the most familiar application to many users, since it deals with where the movement started, i.e. pupils and schools. Chapter 6 deals with the other main application of MLM to date, individual growth and change, and Chapter 7 with meta-analysis. Chapter 8 deals with three level models.

I was tempted to write that Chapter 9 was of particular interest, but then realised that virtually all of the chapters, and especially all of the later chapters, are of particular interest. It describes assessing the adequacy of hierarchical models. It contains practical advice based on all sorts of modelling examples, how to set about building up your model (start by building the level-1 model, and then build the level-2 model on top of that), how to choose what kind of model to fit, what to investigate and how to test the appropriateness of your assumptions.

If Chapters 1-9 are a reprise of their earlier volume emphasising how the authors consider the procedures have improved, Chapters 10-13 break new ground. Chapter 10 deals with non-continuous outcome variables: binary and binomial outcomes, multinomial and ordinal data.

Chapter 11, another particularly exciting chapter, deals with the application of hierarchical models to latent variable models from an HLM approach, using the lowest level to model the relation between the observed variables and the latent data. The chapter covers a wide range of applications, including missing data, measurement error, structural equation modelling, and even a sort of Rasch model.

Chapter 12 deals with cross-classified models. In many ways, the multilevel or hierarchical model is limited. The problem is that no one belongs to only one grouping. Pupils do not just belong to one class, or school, but they are members of families, are associated with playground groupings, live in neighbourhoods, and are members of a family. While from the perspective of the education system and educational research the within school grouping is the most salient, this may not be how the young person sees things, and it may not even be the most important effect differentiating attainment. This represents potentially one of the most important areas for attention in the future.

This is an outstanding book on the topic of multilevel modelling. It's clearly and interestingly written, and I love the way the authors show themselves to be equally at home in the algebra, the social science, and the link between them, and transfer effortlessly between them. Further, not only can (and do) they give you the equations, and their interpretation, but, and this I like particularly, they point out exactly which part of the equation is the one that makes the difference, and how.

One complaint I have is that there are no exercises for the student to strengthen their knowledge muscles. Nor, with a few exceptions, do they provide data sets so that you can reproduce the results of the analyses they describe. This seems to be an increasing and unsatisfactory trend in recent textbooks. I don't understand the rationale for this, as in much the same way as students go to art galleries to try to reproduce paintings, there is nothing quite like trying to reproduce an analysis to internalise something you have just read, and convince yourself that you understand it. One tip I would give to those trying to use it would be to get hold of the HLM program, plus manual. This works its way through many of the data sets and pretty much the same analyses as described in the book.

A rather frightening aspect is that the book is not aimed at statisticians, but rather at social scientists. When some of the UK's leading methodologists do not appear to understand the basics of multilevel modelling, this is unlikely to appeal to many except statisticians in this country- indeed I can think of enough statisticians who would be pushed to follow it. Anyone with a claim to be a quantitative social scientist (or a statistician) and has not read the first edition should try to read at least the first two sections of this book as a duty, and dip into the rest as required.

Some Recent Publications Using Multilevel Models

Baxter-Jones, A. D. G, Helms, P. J., Russell, G., Grant, A., Ross, S., Cairns, J. A. et al. (2000). Early asthma prophylaxis, natural history, skeletal development and economy (EASE). *Health Technology Assessment*, **4**: 1-89.

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Please send us your new publications in multilevel modelling for inclusion in this section in future issues.