

DESIGN EVALUATION AND OPTIMISATION IN CROSSOVER PHARMACOKINETIC STUDIES ANALYSED BY NONLINEAR MIXED EFFECTS MODELS

Thu Thuy Nguyen, Caroline Bazzoli, France Mentré

UMR 738 INSERM - University Paris Diderot, Paris, France

Inserm
Institut national
de la santé et de la recherche médicale

université
PARIS
DIDEROT
PARIS 7

Berlin, 11 June 2010

Population Optimum Design of Experiments Workshop

Outline

- 1 Background & Objectives
- 2 Extension of population Fisher information matrix
- 3 Evaluation by simulation
- 4 Application
- 5 Conclusion

Background

- **Crossover pharmacokinetic (PK) trials**
 - Bioequivalence or interaction trials
- **Approaches for analysis of these studies**
 - Non compartmental : >10 samples/subject \Rightarrow trial in healthy volunteers
 - Nonlinear mixed effects models (NLMEM) : few samples/subject \Rightarrow trial in patients
- **Importance of choice of design in NLMEM**
 - Balance between number of subjects and number of measures/subject, choice of sampling times
 - Impact on the study results (precision of parameter estimates, power of test)
- **Design evaluation et optimisation**
 - Simulations : cumbersome method
 - Population Fisher information matrix (M_F)
 - Calculation of M_F for NLMEM [1,2] : implementation in PFIM [3,4,5]
 - Not applicable for crossover trials

[1] Mentré et al. *Biometrika*, 1997.

[2] Bazzoli et al. *Stat Med*, 2009.

[3] Retout et al. *Comput Methods Programs Biomed*, 2001.

[4] Bazzoli et al. *Comput Methods Programs Biomed*, 2010.

[5] www.pfim.biostat.fr.

Objectives

- To extend M_F for NLMEM with inclusion of within subject variability (WSV) in addition to between subject variability (BSV) and discrete covariates changing between periods
- To compute the expected power for the Wald test of comparison or equivalence and the number of subjects needed (NSN) for a given power
- To implement these extensions in PFIM 3.2
- To evaluate the relevance of these extensions by simulation
- To apply these extensions to design a future crossover study showing the absence of interaction of a compound X on the PK of amoxicillin in piglets

Notations

N subjects $i = 1, \dots, N$

H periods $h = 1, \dots, H$

C : set of discrete covariates c

K_C : set of categories k of c

● Design

- ξ_{ih} = vector of n_{ih} sampling times for subject i at period h
- $\xi_i = (\xi_{i1}, \dots, \xi_{ih}, \dots, \xi_{iH})$ = elementary design of subject i
- $\Xi = \{\xi_1, \dots, \xi_i, \dots, \xi_N\}$ = population design

● NLMEM

Vector of observations of subject i at period h : $y_{ih} = f(\phi_{ih}, \xi_{ih}) + \epsilon_{ih}$

c_{ih} = covariate c of subject i at period h

- ϵ_{ih} = residual error $\sim \mathcal{N}(0, \Sigma_{ih})$; $\Sigma_{ih} = \text{diag}(\sigma_{inter} + \sigma_{slope} f(\phi_{ih}, \xi_{ih}))^2$
- $\phi_{ih} = \mu \exp\left(\sum_{c \in C} \sum_{k \in K_c} \beta_{c_k} \mathbf{1}_{c_{ih}=k} + b_i + \kappa_{ih}\right)$

$$\left. \begin{aligned} \mu &= \text{fixed effect for the reference category} \\ \beta_{c_k} &= \text{fixed effect for the category } k \text{ of } c \text{ (=0 if } k=\text{reference)} \end{aligned} \right\} \rightarrow \theta$$

$$\left. \begin{aligned} b_i &= \text{random effect for subject } i \sim \mathcal{N}(0, \Omega) \\ \kappa_{ih} &= \text{random effect for subject } i \text{ at period } h \sim \mathcal{N}(0, \Gamma) \end{aligned} \right\} \rightarrow v_i$$

- y_i = vector of observations of subject i for all H periods
- $\Psi = (\theta', \lambda')'$: fixed effects, variances of random effects and of residual errors

Extension of M_F

- Elementary M_F for subject i with elementary design ξ_i :

$$M_F(\Psi, \xi_i) = \mathbb{E} \left(\frac{-\partial^2 l(\Psi, y_i)}{\partial \Psi \partial \Psi'} \right)$$

- Log-likelihood (l) approximation using first-order Taylor expansion of the structural model around the expectation of the random effects(=0) :

$$y_i \cong f(g(\theta, 0), \xi_i) + \left(\frac{\partial f'(g(\theta, v_i), \xi_i)}{\partial v_i} \right)_{v_i=0} v_i + \epsilon_i$$

- Expression of $M_F(\Psi, \xi_i)$: diagonal block matrix
(assumption : independence between variance of the observations and fixed effects)

⇒ Population Fisher information matrix : $M_F(\Psi, \Xi) = \sum_{i=1}^N M_F(\Psi, \xi_i)$

⇒ Prediction of standard errors (SE) of discrete covariates fixed or changing between periods from diagonal terms of M_F^{-1}

Prediction of power using M_F

β : covariate effect

Test of comparison

- Test $H_0 : \{\beta = 0\}$ vs. $H_1 : \{\beta \neq 0\}$
- Computing power under H_1 , when $\beta = \beta_1 \neq 0$

$$\beta_1 \xrightarrow{\text{Extension of } M_F} \text{Standard error } SE(\beta_1) \text{ [6]}$$

$$P_{\text{comp}} = 1 - \Phi\left(z_{1-\alpha/2} - \frac{\beta_1}{SE(\beta_1)}\right) + \Phi\left(-z_{1-\alpha/2} - \frac{\beta_1}{SE(\beta_1)}\right)$$

Test of equivalence

- Test $H_0 : \{\beta \leq -\delta \text{ ou } \beta \geq +\delta\}$ vs. $H_1 : \{-\delta < \beta < +\delta\}$ (in general $\delta = 0.2$)
 \Leftrightarrow Schuirmann's TOST $H_{0,-\delta} : \{\beta \leq -\delta\}$ & $H_{0,+\delta} : \{\beta \geq +\delta\}$ [7]
- Computing power under H_1 , when $\beta = \beta_1 \in [-\delta, +\delta]$

$$\beta_1 \xrightarrow{\text{Extension of } M_F} \text{Standard error } SE(\beta_1)$$

$$P_{\text{equi}} = 1 - \Phi\left(z_{1-\alpha} - \frac{\beta_1 + \delta}{SE(\beta_1)}\right) \text{ if } \beta_1 \in [-\delta, 0]; P_{\text{equi}} = \Phi\left(-z_{1-\alpha} - \frac{\beta_1 - \delta}{SE(\beta_1)}\right) \text{ if } \beta_1 \in [0, +\delta]$$

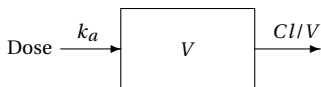
NB : Φ = cumulative distribution function of $\mathcal{N}(0, 1)$ and z_q such as $\Phi(z_q) = q$

[6] Retout et al. *Stat Med*, 2007.

[7] Schuirmann. *J Pharmacokinet Biopharm*, 1987.

Simulation example

- PK model



PK parameters
 $\phi = (k_a, V, Cl)$

- Crossover trials with 2 periods, 1 sequence
 - Period 1 = treatment 1 = A + placebo
 - Period 2 = treatment 2 = A + B
- Treatment effect on Cl : β_{Cl} (interaction of B on A)
- Simulations of 1000 trials with two designs and different values of β_{Cl}

Design	n	N	β_{Cl}
rich (0.5,1,1.5,2,4,6,8h)	7	40	-0.2, 0, 0.1, 0.18, 0.2, 0.4
sparse* (0.5,2,6,8h)	4	40	-0.2, 0, 0.1, 0.18, 0.2, 0.4

* obtained by optimising the rich design of period 1

Evaluation

- For 1000 data sets simulated with each design
 - Estimation of parameters by SAEM algorithm [8,9] in MONOLIX 2.4 [10]
 - Empirical standard error SE_{emp} = sample estimate of the standard deviation from parameter estimates
 - Observed power = proportion of simulated trials for which H_0 is rejected
- By extension of M_F
 - Predicted standard error SE_{M_F}
 - Predicted power from SE of treatment effect parameter

⇒ *Comparison : simulations vs. predictions*

[8] Kuhn and Lavielle. *Comput Stat Data Anal* 2005.

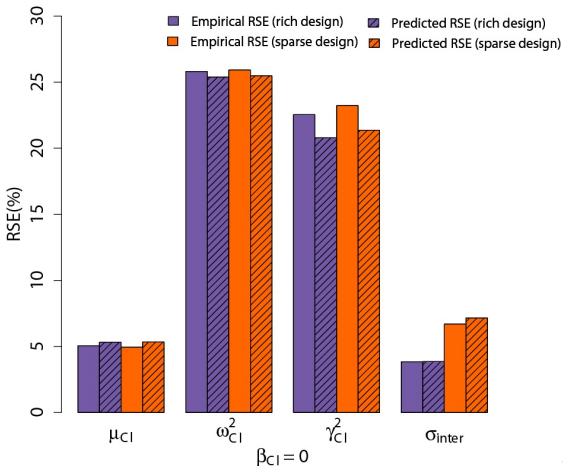
[9] Panhard and Samson. *Biostatistics* 2009.

[10] www.monolix.org

Results

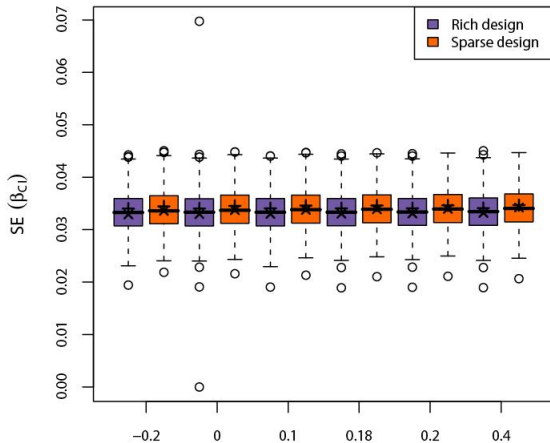
Standard errors

- Relative standard errors (RSE) of parameters



Results

- Boxplots of 1000 $SE(\beta_{CI})$ of each simulated scenario



$\times = SE_{emp}$

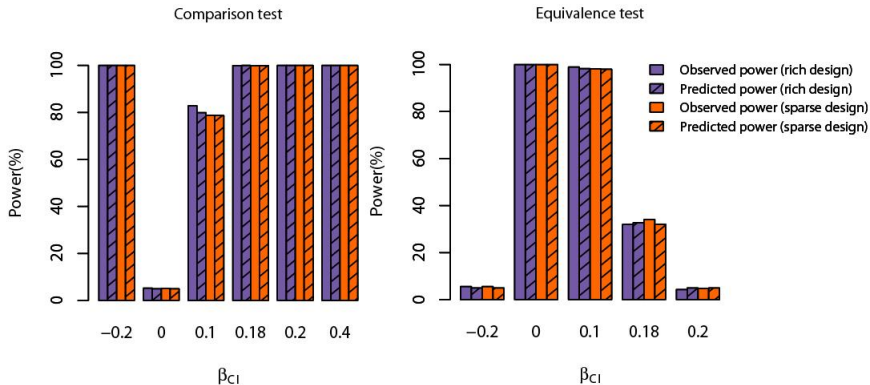
$+ = SE_{MF}$

β_{CI}

Results

Power of the Wald tests of comparison and equivalence

($\alpha = 0.05$ et $\delta = 0.2$)

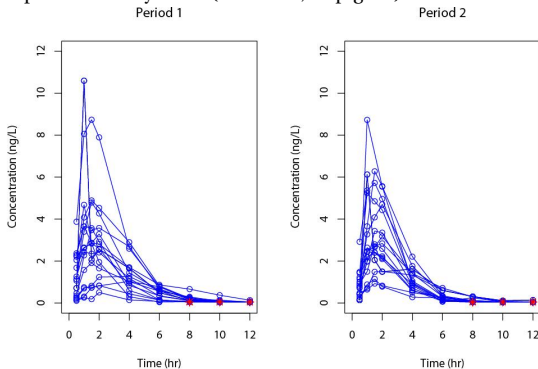


⇒ *Correct predictions by the extension of M_F for SE as well as for test power*

⇒ *Similar results between rich design and optimal sparse design*

Application

- Designing a future study DAV2 [11] on the influence of compound X on the PK of amoxicillin in piglets
 - DAV2 similar design as the simulation study : A = amoxicillin, B = compound X
 - Objective of DAV2 : to show the absence of interaction of X on the clearance Cl of amoxicillin
- Analysis of the previous study DAV1 (crossover, 16 piglets)



[11] www.davolterra.com

Application

- Application of the extension of M_F implemented in PFIM
 - Power of the equivalence test for $N = 16$ piglets
 - Number of subjects needed (NSN) for a given power = 90% with an equivalence limit $\delta = 0.2$

Design	β_{Cl}	Power(%)	NSN
Rich (0.5,1,1.5,2,4,6,8,10,12)	0	41.0	68
Sparse (0.5,2,4,6)	0	40.5	70

⇒ *More piglets to show the absence of interaction of X on the amoxicillin PK in DAV2 with a good power (important within subject variability for $Cl = 45\%$)*

⇒ *Similar results between rich design and optimal sparse design*

Conclusion

Summary

- Relevance of the extension of M_F in NLMEM for crossover trials : correct predictions of standard errors and powers of tests
- Implementation in PFIM 3.2 (several periods, same elementary design at each period)
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Output PFIM 3.2

```
PFIM 3.2 Option 1
Project: EVALUATION EXAMPLE
Date: Fri Apr 02 13:34:05 2010

***** INPUT SUMMARY *****
Analytical function models :
dose/V * ka/(ka - (Cl/V)) * (exp(-(Cl/V) * t)
- exp(-ka * t))
Population design:
Sample times for response: A
              times subjects doses
1 c(0.5, 1, 1.5, 2, 4, 6, 8)      40  30

Number of occasions: 2
Random effect model: Trand = 2
Variance error model response A : ( 0.1 + 0 *f)^2
Covariate model :
NB: Covariates are additive on log parameters
Covariates changing with occasion
Covariate 1 : Treat ( Cl )
      Categories References
(1)      AP      *
(2)      AX
      Sequences Proportions
(1)      AP AX      1

Computation of the Fisher information matrix:
option = 1

***** POPULATION FISHER INFORMATION MATRIX *****
...

***** EXPECTED STANDARD ERRORS *****
----- Fixed Effects Parameters -----
      Beta      StdError      RSE
ka      1.00000000  0.05478405  5.478405 %
V      3.50000000  0.18646491  5.327569 %
Cl      2.00000000  0.10643772  5.321886 %
beta_Cl_Treat_AX 0.09531018 0.03405449 35.730174 %
```

```
----- Variance of Inter-Subject Random Effects -----
      Omega      StdError      RSE
ka      0.09 0.02687382 29.85980 %
V      0.09 0.02526824 28.07583 %
Cl      0.09 0.02285511 25.39457 %

----- Variance of Inter-Occasion Random Effects -----
      Gamma      StdError      RSE
ka      0.0225 0.007998848 35.55044 %
V      0.0225 0.006417971 28.52431 %
Cl      0.0225 0.004679558 20.79804 %

----- Standard deviation of residual error -----
      Sigma      StdError      RSE
sig.interA 0.1 0.003837657 3.837657 %

***** DETERMINANT *****
4.596963e+36

***** CRITERION *****
2152.543

***** COMPARISON TEST *****
      Beta      95 % CI      exp(Beta)      95 % CI
beta_Cl_Treat_AX 0.09531018 [0.029;0.162]      1.1 [1.029;1.176]
Type I error = 0.05
      Expected_power      Number_subjects_needed
      (for a given power=0.9)
beta_Cl_Treat_AX      0.799208      53.65701

***** EQUIVALENCE TEST *****
      Beta      90 % CI      exp(Beta)      90 % CI
beta_Cl_Treat_AX 0.09531018 [0.039;0.151]      1.1 [1.04;1.163]
Type I error = 0.05
Equivalence interval = [log(0.8),log(1.25)]
      Expected_power      Number_subjects_needed
      (for a given power=0.9)
beta_Cl_Treat_AX      0.982525      24.31024

Time difference of 0.05999994 secs
```


Output PFIM 3.2

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- exp(-ka * t))
Population design:
Sample times for response: A
                                times subjects doses
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Number of occasions: 2
Random effect model: Trand = 2
Variance error model response A : ( 0.1 + 0 *f)^2
Covariate model :
NB: Covariates are additive on log parameters
Covariates changing with occasion
Covariate 1 : Treat ( C1 )
      Categories References
(1)      AP      *
(2)      AX
      Sequences Proportions
(1)      AP AX      1

Computation of the Fisher information matrix:
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beta_C1_Treat_AX 0.09531018  0.03405449  35.730174 %
```

Trial with 2 periods

Covariate model

{ AP = amoxicillin+placebo
 AX = amoxicillin+X

SE & RSE of the treatment effect covariate
 (co-administration of amoxicillin with X) on Cl

Output PFIM 3.2

SE and RSE of the within subject variabilities

```
----- Variance of Inter-Subject Random Effects -----
      Omega  StdError  RSE
ka  0.09  0.02687382  29.85980 %
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sig.interA  0.1  0.003837657  3.837657 %
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4.596963e+36
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beta_C1_Treat_AX  0.09531018  [0.029;0.162]  1.1  [1.029;1.176]
Type I error = 0.05
```

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      Expected_power  Number_subjects_needed
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beta_C1_Treat_AX  0.799208  53.65701
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      Expected_power  Number_subjects_needed
                        (for a given power=0.9)
beta_C1_Treat_AX  0.982525  24.31024
```

```
Time difference of 0.05999994 secs
```

90% confidence interval of the covariate effect

Expected power and number of subjects needed
 for the equivalence Wald test

Conclusion

Summary

- Relevance of the extension of M_F in NLMEM for crossover trials : correct predictions of standard errors and powers of tests
- Implementation in PFIM 3.2 (several periods, same elementary design at each period)
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- Studies analysed through NLMEM can be performed with optimal sparse sampling designs
 - requiring the knowledge of the model and its parameters
 - allowing to reduce the number of samples per subject

⇒ *Usefulness of PFIM as an efficient tool for design of bioequivalence/ interaction studies analysed by modelling, avoiding extensive simulations*

Perspectives

- Computation of M_F without linearisation of model
- Different optimisation algorithms