

# Extension of the SAEM algorithm and evaluation of Wald and likelihood ratio tests for interaction or bioequivalence studies

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## Introduction

- Drug interaction studies: are PK of different formulations different? (interaction test  $H_0$ : no difference)
- Bioequivalence studies: are PK of different formulations equivalent? (bioequivalence test  $H_0$ : inequivalence)
- Standard approach (FDA <sup>[1,2]</sup> and EMEA <sup>[3,4]</sup>)
  - Compute AUC and  $C_{max}$  by non compartmental analysis
  - Test on log parameters
  - Needs >10 samples per subject
- Nonlinear mixed effects models
  - Joined data analysis for all subjects
  - Few samples per subject → study on patients

## Objectives

- Adapt and evaluate the SAEM algorithm in MONOLIX software for the analysis of crossover trials
- Develop the likelihood ratio test (LRT) for bioequivalence
- Evaluate by simulation the type I error of Wald tests and LRT

## Methods

- Statistical model
  - Data: individual plasma concentrations under both formulations
  - Estimation
    - Mean PK parameters for the reference formulation
    - Treatment ( $\beta_T$ ), period ( $\beta_P$ ) and sequence ( $\beta_S$ ) effect
    - Between (BSV) and within subject (WSV) variability
- Parameters estimation by maximum likelihood
  - Extension of the SAEM algorithm to estimate WSV (Generalization of <sup>[5]</sup>)
  - Wald test: estimation with the complete model (log likelihood  $L_{all}$ )
  - LRT: estimation with the complete model, with  $\beta_T$  fixed to  $\log(0.8)$  and to  $\log(1.25)$  for the tested parameter (log likelihood  $L_{\log(0.8)}$  and  $L_{\log(1.25)}$ )
- Global test on the treatment effect  $\beta_T$

	Interaction test	Bioequivalence test <sup>[8]</sup>
$H_0$	$\beta_T = \log(0.8)$	$\beta_T \leq \log(0.8)$ or $\beta_T \geq \log(1.25)$
Wald test <sup>[6,7]</sup>	$\log(0.8) \notin CI_{95\%}(\beta_T)$	$CI_{90\%}(\beta_T) \in [\log(0.8); \log(1.25)]$
Reject $H_0$ if		
LRT	$-2 \times (L_{\log(0.8)} - L_{all}) \geq \chi^2(0.95)$	$\beta_T \in [\log(0.8); \log(1.25)]$ $-2 \times (L_{\log(0.8)} - L_{all}) \geq \chi^2(0.9)$ $-2 \times (L_{\log(1.25)} - L_{all}) \geq \chi^2(0.9)$
Reject $H_0$ if		

- Simulation study
  - Theophylline PK: one-compartment model with first order absorption and elimination (parameters  $k_a$ , CI/F, V/F)
  - Designs with 40 subjects: 10 (rich) or 3 (sparse) samples per subject
  - Crossover trials with two or four periods
  - Treatment effect on CI/F and V/F
    - 1000 simulations under  $H_{0,80}$ :  $\beta_{T,CI/F} = \log(0.8)$  and  $\beta_{T,V/F} = \log(0.8)$
    - 1000 simulations under  $H_{0,125}$ :  $\beta_{T,CI/F} = \log(1.25)$  and  $\beta_{T,V/F} = \log(1.25)$
  - Two levels of variability (residual error=10%)

	BSV	WSV
Low	10% for V/F and 20% for $k_a$ and CI/F	BSV/2
High	50%	15%

- Evaluation of the SAEM algorithm: relative bias and RMSE
- Type I error estimation: proportion of rejected  $H_0$

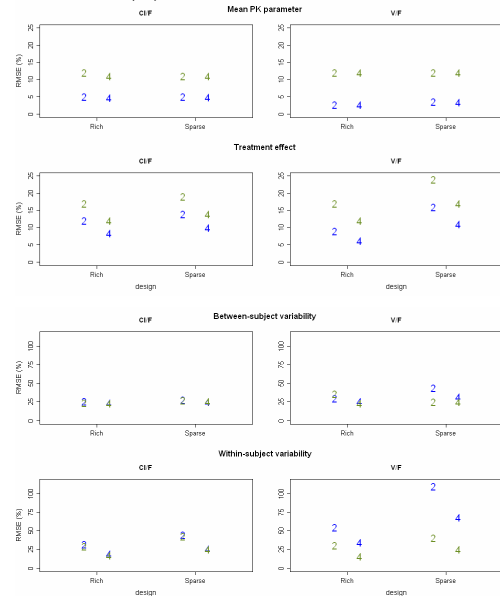
## Results

- Evaluation of the SAEM algorithm (crossover trials with 2 or 4 periods)

- Relative bias (%)

	Rich design	Sparse design
Fixed effect	<2%	<5%
Variance components	<10%	<20%

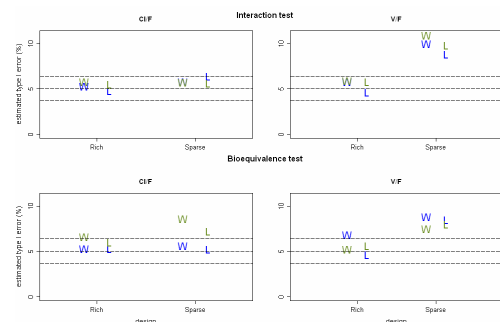
- Relative RMSE (%)



Crossover trials with 2 (2) or 4 (4) periods  
Low variability  
High variability

- RMSE (rich design) < RMSE (sparse design)
- RMSE (4 periods) < RMSE (2 periods)
- RMSE satisfactory except for the WSV on V/F for the low variability and 2 periods

- Type I error (crossover trials with 2 periods)



W: Wald test  
L: LRT  
Low variability  
High variability

Horizontal lines: the nominal level at 5% and its 95% prediction interval for 1000 replicates ([3.7%; 6.4%])

- Type I error at 5% for the rich design
- Slight inflation of the type I error for the sparse design
- Similar results for the Wald test and LRT, and for interaction and bioequivalence tests

## Conclusion

- SAEM algorithm in MONOLIX software
  - Accurate extension for estimation of WSV and crossover trials analysis
- Model-based interaction or bioequivalence tests
  - Good tool applicable to rich and sparse design
  - Good statistical properties under asymptotic conditions

[3] EMEA. Guidance on drug interaction studies (1998)

[4] EMEA. Guidance on investigation of bioavailability and bioequivalence (2001)

[5] Panhard X and Samson A. *Biostatistics*. **10**: 121 (2009)

[6] Panhard X and Mentré F. *Statistics in Medicine*. **24**: 1509 (2005)

[7] Panhard X, Taburet AM, Piketti C and Mentré F. *Statistics in Medicine*. **26**: 1268 (2007)

[8] Schuurmann DJ. *Journal of Pharmacokinetics and Biopharmaceutics*. **15**: 657 (1987)

[1] FDA. Guidance on drug interaction studies (2006)

[2] FDA. Guidance on statistical approaches to establishing bioequivalence (2001)